Sorting out commodity and macroeconomic risk in expected stock returns

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Contents

Introduction

This dissertation consists of three chapters that represent separate papers in the area of asset pricing. The first chapter studies commodity risk and asks how this risk is priced in both stock and futures markets. The second and third chapter study the impact of macroeconomic risk on expected stock returns. The first two chapters are joint work with Frans de Roon and Marta Szymanowska.

The first chapter is motivated by the surge in institutional investment in commodity futures markets since 2003, which has spurred a widespread interest in how these markets are linked to the stock market. Moreover, commodity prices are a risk factor that is an important input to many consumption, production and investment decisions. For this reason, we study the question of whether commodity risk is priced in the stock market and whether this price is time-varying with investor's recently improved access to commodity futures markets.

We develop a model that links the commodity (futures) and stock market through investors that are exposed to commodity risk, but who are initially unable to invest in commodity futures. The model yields three main predictions. First, when investors have no access to commodity futures, the stock market price of commodity risk is negative through investor's cross-hedging demand for stocks that comove with commodity prices. Second, when investors can hedge directly with a futures contract, the stock market price of commodity risk changes and may, in fact, switch sign. In this case, stock market risk is also priced in the futures market, which is the third main prediction. Consistent with these predictions, we find that commodity risk is priced in the stock market, but in opposite ways before and after 2003. Moreover, we indeed find that stock market risk is an important factor in the cross-section of commodity futures returns after 2003.

The second and third chapter are at the intersection of macroeconomics and asset pricing. The second chapter is motivated by the introduction of Treasury Inflation Protected Securities (TIPS), real bonds issued by the United States Treasury, and a poor empirical track record for this important macroeconomic factor. We sort stocks on their exposure to inflation risk and find that there exists an inflation risk premium in the cross-section of US stocks that reverses over time.

We identify empirically the proximate causes of this time-variation and derive a simple model that explains these dynamics. First and foremost, the reversal is driven by the introduction of TIPS in 1997, which are a better hedge for inflation risk than the cross-section of stocks. Second, the inflation risk premium and the effect of TIPS are larger in recessions, when investor's risk aversion is largest. Finally, the time-varying relation between inflation and macroeconomic activity has also contributed to the reversal.

The third chapter is motivated by the observation that an element that is common to most asset-pricing models is often overlooked in empirical tests. This element is time-series and cross-sectional consistency: a factor can only be important in the cross-section of expected returns if it is related to investment opportunties or the real economy in the time-series. Moreover, this time-series relation puts a sign restriction on the factor's risk premium.

This chapter estimates risk premiums in the cross-section of individual stocks for exposure to a range of popular state variables. The chapter finds that these risk premiums are consistent with how these state variables predict macroeconomic activity in the time-series and therefore with investor's incentive to hedge business cycle risk.

The main contribution of this dissertation to the literature is twofold. First, the chapters resuscitate a central role for classical real factors in asset pricing, which have a poor empirical track record relative to a range of empirical factors that lack such a clear economic motivation. Second, the first two chapters identify a new channel through which a factor's risk premium in the stock market varies over time, that is, the introduction of an alternative asset that allows investors to hedge the underlying risk more efficiently. Practically, this dissertation suggests that individual stocks can be used in devising strategies that are exposed to various risks, which is particularly relevant for investors who desire to hedge, because their portfolio is exposed to these risks, or investors who desire to capture risk premiums, by selling this kind of insurance.

I The stock market price of commodity risk

Abstract

We find that commodity risk is priced in the cross-section of US stock returns. Following the Commodity Futures Modernization Act (CFMA) in 2000, investors can hedge commodity price risk directly in the futures market, primarily via commodity index investments, whereas before the CFMA they could gain commodity exposure mainly via the stock market. As a result, we find that the mean return on high-minus-low commodity beta stocks changes from -8% per year pre-CFMA to 11% per year post-CFMA. In addition, as stock market investors increasingly participate in commodity future markets post-CFMA, we find that stock market risk also affects mean commodity futures returns.

Commodity prices are a risk factor that affects consumers, producers and investors alike. Before the passage of the Commodity Futures Modernization Act (CFMA) in December, 2000, (institutional) investors seeking commodity exposure mainly had to do so via (expensive) investments in physical commodities or via commodity-related equity investments. Until then, most investors faced position limits set by the Commodity Futures Trading Commission (CFTC) on traded futures contracts as well as swaps and other over-the-counter derivatives related to commodity futures. This is no longer the case after the CFMA, leading to a strong increase in institutional index investment in commodity futures markets from less than \$ 10 billion in 1998, to \$ 15 billion in 2003, and to \$ 250 billion in 2009 (Irwin and Sanders (2011)).

In this paper, we use this increase in institutional index investment as a quasi-natural experiment that changes the risk-return trade-off in stock and commodity futures markets. In particular, we analyze the effect of commodity risk on expected stock returns, as well as the effect of increased commodity index investment following the CFMA on pricing in stock and commodity futures markets.

We develop a model in the spirit of Hirshleifer (1988, 1989) that establishes an important link between these markets. We model investors that are exposed to commodity price risk, for instance because high commodity prices feed into inflation or because they predict consumption-investment opportunities with a negative sign, and producers that maximize utility over income from these commodities, which they hedge in the futures market. When investors cannot hedge their commodity price risk in the futures market, but need to do so using stocks highly correlated with commodities, a hedge portfolio of high-minus-low commodity beta stocks will command a negative risk premium.

When investors are able to hedge directly with a futures contract, the hedging premium in the stock market goes to zero if the contract is used exclusively for hedging. When the futures contract is attractive from an investment (or, speculative) point of view as well, our model indicates a reversal in the stock market price of commodity risk and an increasing role of stock market risk in explaining the cross-section of commodity futures returns. We derive plausible conditions similar to Hirshleifer (1988, 1989) for a positive speculative investment in commodity futures to be optimal: the presence of sufficiently many producers relative to investors (speculators) and producers that are sufficiently more risk averse than investors.

Empirically, we find that commodity risk is priced in the cross-section of stock returns, but in opposite ways before and after the CFMA. Sorting stocks according to their beta with respect to a broad index of 33 commodity futures, we find a cross-section of expected returns that cannot be explained by the traditional portfolio return-based asset pricing models.[1] Pre-CFMA, high commodity beta stocks underperform by about -8% in average returns, which translates into -11.5% to -8.5% in risk-adjusted returns. Post-CFMA, this performance reverses to around 11% in both average and risk-adjusted re-

[1] These are the CAPM (Sharpe (1964), Lintner (1965) and Mossin (1966)), the Fama-French three-factor model (Fama and French (1993)), and the Fama-French-Carhart model (Carhart (1997)). Although unreported, our conclusions are unchanged when adding the liquidity factor of Pastor and Stambaugh (2003).

turns. The magnitude of these returns is similar to other sorts reported in the literature, such as momentum (Jegadeesh and Titman (1993)).

Likewise, stock market risk does not show up in the cross-section of commodity futures returns Pre-CFMA, but we do find evidence that stock market risk is a priced factor in this cross-section Post-CFMA.

As discussed in Lewis (2007), the most common approach for institutional investors to gain commodity exposure has historically been via equity investments. However, with the emergence of commodity index-based products, these products have become the most popular route. Figure 1 illustrates this surge in commodity investments. The figure plots total open interest in 33 commodities over time (200312 = 100) in US \$ and the number of contracts outstanding. For both measures we see that open interest increases to record-high levels in each sector around 2003 without ever returning to historical levels. Even more important for our analysis, the share of total open interest in the futures market that is attributable to institutional index investment has grown from around 10% in 2003 (\$ 15 billion) to 40% in 2009 (\$ 250 billion) (Irwin and Sanders (2011)). In line with the conditions mentioned above, we show that these index investments are well-accommodated by traditional hedgers in futures markets (see also Stoll and Whaley (2009) and Cheng et al. (2011)).

Our findings contribute to the literature on cross-sectional asset pricing and commodities. Our first contribution is to establish an important link between stock markets and commodity (futures) markets. These markets were previously thought to be segmented, given that the traditional portfolio return-based stock market factors play a weak role, if any, in explaining the cross-section of commodity futures returns (see, e.g., Dusak (1973), Bessembinder (1992), Bessembinder and Chan (1992) and Erb and Harvey (2006)). We show that, conversely, commodity risk does play a role in explaining the cross-section of stock returns and that stock market risk plays a role, Post-CFMA, in explaining the cross-section of futures returns. Our results imply that the two markets are linked due to investor's need to hedge commodity risk Pre-CFMA and, in addition, their speculative demand in commodity futures markets Post-CFMA. Thus, our findings are also an important addition to papers that investigate the financialization of commodity futures markets (see, e.g., Tang and Xiong (2012), Irwin and Sanders (2011), Stoll and Whaley (2009), Buyuksahin et al. (2010), Buyuksahin and Robe (2010), Cheng et al. (2011), and Basak and Pavlova (2013)).

We find that the reversal is driven by commodities from the Energy and (Precious) Metals sectors, consistent with the fact that the largest share of index investment is flowing into these sectors. Also, we show that the commodity premium in the stock market, and its reversal, show up using only the between-industry or only the within-industry variation in commodity betas. This finding indicates that within-industry variation, due to, for instance, corporate hedging practices, market power, or the place of a firm in the supply chain, is priced in addition to the pricing of between-industry variation due to differences in fundamental exposures to certain commodities. In fact, our regression-based measure of commodity risk essentially controls for the fact that some firms hedge (or unhedge) their exposures and therefore provides for a more natural measure of commodity risk than looking at SIC codes alone, as in Gorton and Rouwenhorst (2006).

In the next section, we derive a model that links stock and commodity (futures) markets. Section 2 describes the institutional background, the data and method. Section 3 presents returns along the cross-section of commodity exposures. In Section 4 we analyze sector and industry effects as well as the relation between inflation and commodity risk. Section 5 summarizes and concludes.

1 Theoretical framework

We start out by developing a model that links the commodity market to the stock market. We initially think of the commodity as a basket of commodities, that is, an index. Our model uses a standard two-date mean-variance framework in the spirit of Hirshleifer (1988, 1989) and Bessembinder and Lemmon (2002). An important difference with these papers is that we do not model the stock market as one security, rather we model it as consisting of multiple stocks. The markets are linked through (institutional) investors that are exposed to commodity risk, but do not invest in commodity futures initially. We will see that the cross-hedging demands of these investors in the stock market imply a commodity risk premium in the cross-section of stocks. Mimicking the recent influx of institutional investment in commodities, the model shows how changing participation in the futures market by these same investors may impact the stock market price of commodity risk.

A Economic setting

There are three types of agents: N_P commodity Producers that can hedge their commodity risk in the futures market, N_S specialized Speculators that only trade in the futures market, and N_I Investors that initially only trade in the stock market. Producers and Speculators only trade in the futures market and not in the stock market. Similar to Hirshleifer (1988) this element of segmentation can be motivated with trading costs, in the form of explicit charges or the costs of becoming informed, or because of wealth restrictions. Investors initially do not trade in the futures market, which is consistent with narrow position limits set by the CFTC for this class of traders to prevent "excessive speculation" historically.

B The stock market with Investors facing position limits in the futures market

In this subsection, we derive equilibrium demand and expected returns in the stock market. There are N_I Investors that are each endowed with one dollar that they can invest in the risk free asset, with return $R_{f,t}$, and K risky stocks, with excess return vector r_{t+1}. These Investors may also want to add the futures contract, with (pseudo-) return $R_{Fut,t+1}$, but may be prevented from doing so because of position limits, which were historically imposed by the CFTC. We first model the case with position limit, such that Investors cannot take a position in the futures market. Subsequently, we model the case without position limit, when Investors can optimally choose their position in the futures contract.

We write the portfolio return of the Investors exposed to commodity price risk as

$$y_{I,t+1} = R_{f,t} + w_r' r_{t+1} + w_{Fut} R_{Fut,t+1} + \varphi R_{S,t+1}. \tag{1}$$

Here, w_r is the K-dimensional vector of weights in stocks, w_{Fut} is the position in the futures contract and φ is the size of the exposure to spot commodity price risk $R_{S,t+1}$ per dollar invested. This exposure can be motivated in (at least) three ways. First, Investors are exposed to inflation risk and commodity prices represent a large and volatile component of inflation. Second, commodity prices are a state variable for many investment, production and consumption desisions. Finally, in the model of Basak and Pavlova (2013), Institutional investors care about their performance relative to a commodity index, such that marginal utility increases in the performance of the index. This assumption can be approximated by setting $\varphi = -1$, such that the agent solves a mean-variance utility problem in relative returns.

In the presence of position limits, investors choose the optimal portfolio of stocks alone: $w = (w_r'\ 0)'$, whereas in the absence of position limits they can add a futures position: $w = (w_r'\ w_{Fut})'$. Likewise, $\mu = (\mu_r'\ \mu_{Fut})'$ is a $K+1$ vector of expected excess stock returns and the expected futures return, Σ is their corresponding $(K+1)\times(K+1)$ covariance matrix and $\Sigma_S = (\Sigma_{rS}'\ \sigma_{FS})'$ is the corresponding $K+1$ vector of covariances with the spot commodity return. Assuming that relative risk aversion γ_I is homogenous, Investors solve the following mean-variance utility problem in the two separate cases

$$\textbf{With limits} \max_{w_r} w_r'\mu_r - \frac{\gamma_I}{2}\left\{w_r'\Sigma_{rr}w_r + 2w_r'\Sigma_{rS}\varphi + \varphi^2\sigma_{SS}\right\} \quad (2)$$
$$\textbf{Without limits} \max_{w} w'\mu - \frac{\gamma_I}{2}\left\{w'\Sigma w + 2w'\Sigma_S\varphi + \varphi^2\sigma_{SS}\right\}.$$

In order to express the optimal portfolio weights, we assume the futures contract is perfectly correlated with the commodity return and for simplicity that the two returns have equal variances, i.e., $\sigma_{FF} = \sigma_{SS} = \sigma_{FS}$.[2] Using the above assumptions, the partitioned inverse of Σ, and the auxiliary regression of the futures return on the stocks

$$R_{Fut,t+1} = a + b'r_{t+1} + e_{t+1}, \text{ with} \quad (3)$$
$$\sigma_{ee} = Var(e_{t+1}), \quad (4)$$

Appendix A shows that the optimal portfolio in the two cases is

$$\textbf{With limits } w_r = \gamma_I^{-1}\Sigma_{rr}^{-1}\mu_r - \varphi\Sigma_{rr}^{-1}\Sigma_{rS}, \quad (5)$$
$$\textbf{Without limits } w_r = \gamma_I^{-1}\Sigma_{rr}^{-1}\mu_r - w_{Fut,spec}\Sigma_{rr}^{-1}\Sigma_{rS} \quad (6)$$
$$w_{Fut} = w_{Fut,spec} - \varphi, \text{ with} \quad (7)$$
$$w_{Fut,spec} = \frac{1}{\gamma_I}\frac{a}{\sigma_{ee}}. \quad (8)$$

In the presence of position limits, the optimal demand for stocks in Equation (5) combines a standard speculative demand (the tangency portfolio) with a minimum-variance hedge demand for commodity risk,

[2]This perfect correlation is true conditionally. Further, we only need a perfect correlation for expositional purposes: the hedge demand will tilt towards the futures contract as long as it is a better hedge than the available stocks, such that the model's main implications go through. The assumption of equal variances is a matter of scaling alone.

which is similar to Merton (1973) and Anderson and Danthine (1981), for instance. The hedge demand is defined over the coefficients from a regression of $R_{S,t+1}$ on r_{t+1}: $\Sigma_{rr}^{-1}\Sigma_{rS}$ and the exposure φ. If $\varphi < 0$ ($\varphi > 0$), Investors adjust upward their demand for high (low) commodity beta stocks in order to hedge.

Without position limits, the optimal futures demand in Equation (7) combines a speculative demand with a hedge demand. The hedge demand φ focuses completely on the futures contract, because $r_{Fut,t+1}$ is perfectly correlated with the commodity return $R_{S,t+1}$. Thus, hedging of commodity risk takes place entirely via the futures market and no longer via a cross-hedging demand in the stock market. For instance, Investors go long in the futures contract to hedge when $\varphi < 0$. The speculative demand for futures $w_{Fut,spec} = \gamma_I^{-1}\sigma_{ee}^{-1}a$ is a standard speculative demand for the futures contract given that it is hedged with the stocks using Equation (3). Here, a is a (generalized) Jensen measure of the futures contracts versus the available stocks. A positive a, combined with low enough residual risk σ_{ee}, implies positive diversification benefits from adding a long position in the futures contract to the stock portfolio and therefore a positive speculative demand.

Finally, Equation (6) demonstrates that the optimal demand for stocks, w_r, adjusts the tangency portfolio with a minimum-variance hedge demand defined over the speculative demand for futures $w_{Fut,spec}$. Thus, if the agent seeks additional exposure to futures (beyond the hedge demand φ) when $a > 0$, he will hedge this additional exposure among the K risky assets. This result follows directly from the tangency portfolio of the extended set of assets, as shown in Stevens

(1998). Importantly, the composition of this hedge portfolio is determined by $\Sigma_{rr}^{-1}\Sigma_{rS}$, as in the case with a position limit.

Because only Investors participate in the stock market, w_r in Equation (5) and (6) is the market portfolio of stocks w_m. Using this, Appendix A shows

Proposition 1 *When Investors are exposed to commodity risk and face possible position limits in the futures market, expected excess stock returns depend on their covariance with the market portfolio ($r_{m,t+1}$) and the commodity return ($R_{S,t+1}$):*

$$\begin{aligned} \textbf{\textit{With limits}}\ E(r_{k,t+1}) &= \gamma_I \sigma_{km} + \gamma_I \varphi \sigma_{kS} && (9) \\ \textbf{\textit{Without limits}}\ E(r_{k,t+1}) &= \gamma_I \sigma_{km} + \gamma_I w_{Fut,spec} \sigma_{kS}. && (10) \end{aligned}$$

Propostion 1 shows that expected stock returns depend on their covariance with the market portfolio as well as on their covariance with the commodity return, due to the hedge demand. The effect of commodity hedging on expected returns is different in the two cases. When the Investor faces a position limit, he cannot hedge the exposure to commodity risk φ directly in the futures market, such that cross-hedging demands in the stock market are optimal. As a result, commodity risk is priced in the stock market and the price per unit of covariance is $\gamma_I \varphi$. Thus, if $\varphi < 0$, the price of commodity risk is negative: Investors adjust upward the demand for stocks that move in-sync with the commodity, because these stocks are attractive as a hedge, which increases (decreases) their equilibrium price (expected excess return). Conversely, if $\varphi > 0$, the stock market price of commodity risk is positive.

When there are no position limits in the futures market, Investors hedge their exposure to commodity risk directly using the futures contract. Consequently, φ no longer affects expected stock returns. However, if there is a speculative demand (long or short) for commodity futures when a is non-zero, Investors hedge this speculative demand in the stock market. Thus, commodity risk is again priced in the cross-section of stock returns. The size and sign of the commodity risk premium in the two cases depends on the size and sign of $\gamma_I \varphi$ versus $\gamma_I w_{Fut,spec}$.

C The futures market

In this subsection, we derive the optimal futures demand for Producers and Speculators and analyze the impact of lifting the position limits initially faced by Investors on the futures risk premium.

With position limits, there are two classes of traders that participate in the futures market: Producers and Speculators. The N_P Producers are each endowed with one dollar with which they (each) produce q_{t+1} units of a commodity. The amount produced is stochastic and has expectation one, but is assumed to be the same for each producer. Thus, total endowed wealth of the Producers is N_P and total (stochastic) output of the commodity is $Q_{t+1} = N_P q_{t+1}$. Consumers are characterized by the inverse demand function for the commodity: $Q^D_{t+1} = g(S_{t+1})$, such that spot market equilibrium implies $Q_{t+1} = Q^D_{t+1}$. We normalize the Producer's problem similar to Investors, such that he maximizes a mean-variance utility function over his portfolio return

$$y_{P,t+1} = q_{t+1} R_{S,t+1} + h R_{Fut,t+1}, \tag{11}$$

which combines the uncertain return from output ($q_{t+1} R_{S,t+1}$) with a hedge position in h futures contracts. Assuming again that relative risk aversion is homogenous, each Producer solves the problem

$$\max_{h} \; E(y_{P,t+1}) - \frac{\gamma_P}{2} V(y_{P,t+1}). \tag{12}$$

Using the notation introduced before and the assumption that $\sigma_{FF} = \sigma_{SS} = \sigma_{FS}$, Appendix B shows that a Taylor series approximation of total output Q_{t+1} around its expected value $\overline{Q} = N_P \bar{q}$, results in the optimal futures position

$$h = \frac{\mu_{Fut}}{\gamma_P \sigma_{FF}} - (1+\eta) \frac{\sigma_{FS}}{\sigma_{FF}}, \tag{13}$$

where $\eta = g\left(\overline{Q}\right) / \overline{Q} g'\left(\overline{Q}\right)$ is a demand elasticity, as in Hirshleifer (1988), and $\sigma_{FF}^{-1} \sigma_{FS} = 1$ as assumed before. Equation (13) is a well-known result that separates the optimal futures position in a speculative demand and a pure hedge demand. The pure hedge demand reflects both price and quantity risk by adjusting the futures position according to the demand elasticity.

The N_S Speculators are likewise endowed with one dollar each, which they invest in the risk free asset and s futures contracts. Thus, Speculators maximize a mean-variance utility function over their portfolio return

$$y_{S,t+1} = R_{f,t} + s R_{Fut,t+1}. \tag{14}$$

Assuming again that relative risk aversion is homogenous, the optimal futures position for each Speculator equals

$$s = \frac{1}{\gamma_S} \frac{\mu_{Fut}}{\sigma_{FF}}, \tag{15}$$

which is analogous to the speculative demand by Producers.

Without position limits, there are three classes of traders in the futures market: Producers, whose demand is given in Equation (13), Speculators, whose demand is given in Equation (15) and Investors, whose demand is given in Equation (7). Since futures contracts are in zero net supply, futures market equilibrium requires for the two cases

$$\begin{aligned} \textbf{With limits } 0 &= N_P h + N_S s & (16) \\ \textbf{Without limits } 0 &= N_P h + N_S s + N_I w_{Fut}. & (17) \end{aligned}$$

Using these market clearing conditions, Appendix C shows

Proposition 2 *In a futures market where Investors face possible position limits, the futures risk premium equals:*

$$\begin{aligned} \textbf{\textit{With limit}}\ E(R_{Fut,t+1}) &= \frac{\lambda_P}{\lambda_P + \lambda_S} \gamma_P (1+\eta) \sigma_{FS} & (18) \\ \textbf{\textit{Without limit}}\ E(r_{Fut,t+1}) &= \frac{\lambda_P \gamma_P (1+\eta) + \lambda_I \gamma_I \varphi}{\lambda_P + \lambda_S + \tilde{\lambda}_I} \sigma_{FS} & (19) \\ &+ \frac{\tilde{\lambda}_I \gamma_I}{\lambda_P + \lambda_S + \tilde{\lambda}_I} \sigma_{FT} & (20) \\ \lambda_i &= N_i / \gamma_i, i = P, S, I & (21) \\ \tilde{\lambda}_I &= \lambda_I \frac{\sigma_{FF}}{\sigma_{ee}}, & (22) \end{aligned}$$

where σ_{FT} denotes covariance with the tangency portfolio of stocks only, with weights $w_{Tan} = \gamma_I^{-1} \Sigma_{rr}^{-1} \mu_r$ and excess return $r_{Tan,t+1}$.

Thus, when only Producers and Speculators participate in the futures market, the futures risk premium depends on the covariance of the futures and the spot return σ_{FS}, the risk aversion of the Producers γ_P, and the risk aversion-adjusted market share of Producers in the futures market, $\lambda_P / (\lambda_P + \lambda_S)$. The term $\gamma_P (1 + \eta) \sigma_{FS}$ reflects the hedge demand for futures contracts by Producers. This hedge demand is increasing in the covariance of the futures with the spot, adjusted for the demand elasticity, and in Producer risk aversion. With $\eta > -1$, the hedge demand will be a short position, and the futures risk premium will be positive. This finding is the familiar hedging pressure effect: a short hedge position has to be compensated by the speculative demand from Speculators and Producers themselves. This speculative demand can only be a long position if the futures risk premium is positive. The risk adjusted market share of the Producers versus Speculators reflects the strength of the hedging pressure effect: when there are more Speculators or their risk aversion is lower, there is a bigger speculative demand to absorb the hedge demand of Producers, thereby lowering the futures risk premium.

When the position limits for Investors are lifted, the futures risk premium in Equation (19) contains a hedging pressure effect similar to Equation (18), except that now also Investors enter both the numerator and the denominator. Investors hedge commodity risk in the futures market, which adds to the hedging pressure effect by an amount $\lambda_I \gamma_I \varphi$. If $\varphi < 0$, the long hedge demand of Investors (partly) offsets the hedge demand by Producers, thus lowering the futures risk premium. Even if Investors do not have an exposure to commodity risk, i.e., $\varphi = 0$, they enter the first term via the denominator, thereby lowering the futures risk premium. This effect is similar to the presence of Speculators.

The second term in Equation (19) follows from the fact that Investors combine the futures contract with the stocks for speculative reasons. This makes stock market risk priced via the covariance of the futures return with the return on the tangency portfolio of stocks, w_{Tan}. Since only Investors invest in both stocks and futures, the weight assigned to this stock market risk is the risk aversion weighted market share of Investors in the futures market. Because Investors care about the residual risk of the futures σ_{ee} rather than total risk σ_{FF}, their market share λ_I is adjusted for this according to Equation (22).

2 Empirical framework

A Institutional setting

The model outlined above relies on an assumption that a structural break must have occurred in the investment practices of a large group of agents (Investors). We argue that this break occurred following the passage of the CFMA on December 21, 2000. The act allowed institutional investors (insurance companies, pension funds, foundations and hedge funds e.g.) and wealthy individuals to take large positions in commodity futures and other commodity derivatives, whereas before 2000 most of them faced narrow position limits imposed by the CFTC to prevent "excessive speculation".

In terms of our model, this means that Investors could not hedge their commodity risk exposure in the futures market historically, but had to resort to hedging in the stock market or to directly investing in physical commodities, which is expensive (Lewis (2007)). After the CFMA, Investors can get the desired commodity exposure directly via futures (and other commodity derivatives) markets. As a result, commodity index investment by such investors in over-the-counter swap agreements, exchange-traded funds (ETF), exchange-traded notes (ETN), and managed funds, benchmarked to well-diversified and transparent indices like the SP-GSCI and DJ-UBSCI, jumped from \$ 15 billion in 2003 to \$ 250 billion at the end of 2009, which translates to an increase from 10% to over 40% in the share of commodity futures market open interest attributable to institutional investors (Irwin and Sanders (2011)). These numbers underestimate the true investments in commodities, because the exchange-traded market still represents less than 10% of the total market for commodity derivatives (Etula (2010)).

In line with, among others, Domanski and Heath (2007) and Tang and Xiong (2012) we use the observable change in total open interest seen in Figure 1 to motivate splitting our sample at December 31, 2003. We refer to the period before December 31, 2003 as "Pre-CFMA" and the period thereafter as "Post-CFMA". Below we show that our results are not sensitive to the exact breakpoint chosen.

B Commodity futures data

We construct an index of commodity futures to represent the futures contract modeled in Section 1. We collect data on prices and open interest of 33 exchange-traded, liquid commodities from the Commodity

Research Bureau (CRB), supplemented with data from the Futures Industry Institute (FII). A detailed overview of the sample is given in Table I. The commodities are divided into four broad sectors: Energy, Agriculture, Metals and Fibers, and Livestock and Meats.[3]

Table I about here.

We calculate futures returns using a roll-over strategy of first and second nearest-to-maturity contracts.[4] First, we focus on contracts that are relatively close to maturity, because these are most liquid. Second, this strategy is similar to the construction of commercial indexes, like the SP-GSCI and the DJ-UBSCI. We roll out of the first nearest contract (and into the second nearest contract) at the end of the month before the month prior to maturity. In this way, we guard against the possible confounding impact of erratic price and volume behavior commonly observed close to maturity.[5] For the Energy sector we have contracts maturing in all months of the year; for most other commodities we have between four and eight delivery months available. For all contracts except Sugar and Pork Bellies, the delivery months are never more than three months apart.

Table I reports average returns, standard deviations (both in annualized percentages) and median total open interest (TOI) in US$

[3] For instance, Hong and Yogo (2012) use a similar partitioning.

[4] To be precise, we calculate uncollateralized futures returns in month t, as $R_t = \frac{F_{t,T}}{F_{t-1,T}} - 1$, where $F_{t,T}$ is the futures price at the end of month t of the nearest contract whose expiration date T is after the end of month $t+1$. These uncollateralized futures returns are comparable with excess returns on stocks and are made up of both the spot return and the roll return.

[5] By rolling over approximately one to two weeks before most commercial indices do, our index is not affected by their short-term market impact, which may partly cause this erratic behavior (Muo (2010)).

for each individual contract.[6] Historically, the Energy (Livestock and Meats) sector has contained the largest (smallest) commodities in open interest and trading volume. Throughout, we focus on an open interest-weighted total index (OIW) that aggregates all 33 commodities. Similar to value-weighted stock indices or production-weighted commercial commodity indices, OIW weights month t commodity returns according to TOI at the end of month $t-1$. We show that the main results are robust for an equal weighted total index as well as the SP-GSCI Excess Return Index and present additional evidence for OIW sector indexes.

C Estimating commodity exposures

To find out whether commodity prices are a relevant risk factor in the stock market, we apply the Fama and French (1992, 1993, 1996) portfolio approach. We sort both individual stocks (that is, all ordinary common shares traded on NYSE, AMEX and NASDAQ excluding financial firms) and 48 industry portfolios on their beta with respect to the OIW commodity index.[7]

At the end of each month $t-1$, we re-estimate the commodity beta for stock (or industry) i, $\beta_{i,t-1}$, over a 60-month rolling window using

$$R_{i,s} - R_{f,s} = \alpha_{i,t-1} + \beta_{i,t-1} R_{oiw,s} + \varepsilon_{i,s}, \text{ for } s = t-60, ..., t-1, \quad (23)$$

where we require that at least three out of the last five years of returns are available. We apply Equation (23) from January 1975 onwards to

[6] TOI is defined as the sum of the open interest of all outstanding contracts (i.e., contracts with different maturities) for a specific commodity, multiplied by the first-nearest futures price.

[7] The 48 industry portfolios are sourced from Kenneth French's Web site.

ensure that the OIW total index consists of at least 20 commodities, such that it can be reasonably expected to mimic the important macroeconomic impact that commodities have. As a result, the sample of post-ranking portfolio returns spans from January 1980 to December 2010, which we split into a period of 288 months Pre-CFMA and 84 months Post-CFMA. In a robustness check, we control for the benchmark factors of the CAPM (Sharpe (1964), Lintner (1965) and Mossin (1966)), the three-factor model of Fama and French (1993, denoted as FF3M) and the four-factor model of Carhart (1997, denoted as FFCM) when estimating commodity beta.

First, we construct market value-weighted stock portfolios from both a one-dimensional sort in five commodity beta groups and an independent, two-dimensional sort in five commodity beta and five size groups. Second, we perform a one-dimensional between-industry sort, which constructs five industry-portfolios that equally weight nine or ten industries each. We apply the time-series regression approach of Black et al. (1972) to analyze average returns and risk-adjusted returns (relative to the CAPM, FF3M and FFCM) of the portfolios introduced above as well as the High minus Low commodity beta (HLCB) spreading portfolios constructed therefrom.

D Expected commodity futures returns

Although the model of Section 1 contains only one commodity, the commodity futures risk premium in Proposition 2 can be generalized to multiple commodities, which provides us with a set of predictions for the cross-section of expected commodity futures returns.[8]

First and foremost, we focus on the prediction that in the absence of position limits for Investors, stock market risk is a priced factor in commodity futures (Equation (19)). This focus is motivated by evidence that suggests stock market risk, as measured by MKT, SMB and HML, is not priced in commodity futures historically. This finding is consistent with our model, because institutional investors did not enter commodity futures markets en masse until after the CFMA. In our model, stock market risk is defined as covariance with the tangency portfolio of stocks, which combines the market portfolio and the hedge portfolio for commodity risk (see Equation (5) and (6)). Accordingly, we sort commodity futures one-dimensionally at the quartiles of ranked covariance with each of the two portfolios.

Proposition 2 also implies that a hedging pressure effect is present in futures returns both with and without position limits. Hence, we also sort on a hedging pressure variable, using a smaller cross-section (26 commodities) and time-series (1986 to 2010), dictated by the availability of public CFTC data. Following, Basu and Miffre (2013), hedging pressure is calculated as a 12-month moving average of the difference between the number of short and long positions of commercial hedgers relative to their total position.[9] These results need to be interpreted with caution, however, because (i) there are classification errors in the

[8]Note, this generalization requires segmentation between the commodity markets for the Producers and Speculators, which can be motivated by (explicit or implicit) trading costs as in Hirschleifer (1988, 1989). Moreover, because Investors are present in all futures markets, the returns on futures $l = 1, .., L$ must be independent conditional on the stock returns, otherwise the generalization is only approximate.

[9]Unlike the model in Section 1 this allows Producers (hedgers) to take both long and short positions in futures contracts, but we show in the Internet Appendix that the model is easily extended by allowing Producers to have either long or short exposures.

CFTC data (see, e.g., Cheng et al. (2011) and Acharya et al. (2013)) and (ii) these data do not contain the hedging positions for Investors that we need to measure hedging pressure in the exact manner suggested by our model in the Post-CFMA period.

3 The cross-section of stock and futures returns

We start out by documenting the main implications of the model, which are summarized in Propositions 1 and 2 of Section 1. First, commodity risk is priced in the stock market and this price changes Post-CFMA. Second, stock market risk is priced in the futures market, but only Post-CFMA.

A Commodity risk in the stock market

Our first main results are presented in Table II. Here, we analyze whether a commodity risk premium is present in the cross-section of stock returns and test if the risk premium varies over the two subperiods. We present average returns and standard deviations for the period Pre-CFMA and Post-CFMA in Panel A and Panel B, respectively, whereas Panel C tests the difference in average returns.

Table II about here.

In average returns, stocks and industries with high commodity betas underperform consistently Pre-CFMA. Also, for all size quintiles except the smallest, average returns are decreasing monotonically in commodity beta. The High minus Low Commodity Beta (HLCB) spread is economically large and statistically significant at -8.11%

for the one-dimensional sort of stocks and at -4.72% for industries.[10] On the contrary, high commodity beta stocks outperform consistently Post-CFMA. Average returns increase monotonically in commodity beta in all control groups, which adds up to a HLCB spread that is economically large and statistically significant at 12.08% for the one-dimensional sort of stocks and at 12.22% for industries. In both sub-periods, portfolio standard deviation increases almost monotonically in commodity beta, which is consistent with the idea that commodity beta captures an exposure to risk.

Finally, the results in Panel C demonstrate that the difference in average returns between the two sub-periods is highly significant around 20% for the HLCB portfolio of individual stocks and 17% for the HLCB industry portfolio. Moreover, going from Low to High among the long-only portfolios, we see that the difference is increasing monotonically in commodity beta. Highlighting the importance of controlling for size, we find that the reversal is strongest among the bigger stocks in both sub-periods.

Table III about here.

Next, we see in Table III that the previously documented performance-beta relation and its reversal are robust when controlling for the usual risk factors. Table III is structured similarly to Table II except that we now present risk-adjusted returns (alphas) for the two sub-periods in Panels A and B, respectively. Pre-CFMA, the HLCB spread actu-

[10] We find Construction, Steel Works (etc.), Petroleum and Natural Gas, Precious Metals, Mining, Coal and Machinery among the industries with consistently high commodity betas and Retail, Insurance and Consumer Goods among the industries with consistently low commodity betas.

ally widens to large and significant CAPM, FF3M and FFCM alphas of between -8% and -10% for the one-dimensional sort of stocks and around -6% for industries. Post-CFMA, only about 2% of the HLCB spread is captured by the MKT factor, leaving HLCB alphas that are over 10% for both stocks and industries. Again, in almost every case the alphas are monotonically decreasing Pre-CFMA and increasing Post-CFMA in commodity beta. Panel C summarizes this evidence and shows that the difference in the two commodity risk premiums adds up to an economically large and highly significant difference of about 20% for stocks and 17% for industries.

The reversal from a negative to a positive commodity risk premium reported above is consistent with our model. Pre-CFMA, when institutional investors hedge their commodity risk in the stock market, Equation (9) implies that the commodity risk premium is negative when the fundamental exposure $\varphi < 0$. Post-CFMA, when commodity futures represent a considerable fraction of many institutional investors' portfolios, Equation (10) implies that the commodity risk premium is zero when these positions solely reflect a hedge demand, i.e., $w_{Fut,spec} = 0$, and positive when these positions also reflect a speculative demand, i.e, $w_{Fut,spec} > 0$.

A negative fundamental exposure is consistent with (i) investor's incentives to hedge inflation, which risk premium is also negative (see, e.g., Chen et al. (1986) and Ferson and Harvey (1991)), and (ii) the interpretation of commodity prices as a state variable. For instance, Driesprong et al. (2008) and Jacobsen et al. (2013) find that energy and metals prices predict stock market returns with a negative sign over our sample period, such that the Intertemporal CAPM of Merton (1973) implies a negative risk premium. Moreover, Hamilton (2008) notes that "Nine out of ten of the U.S. recessions since World War II were preceded by a spike up in oil prices", such that oil (and other Energy) prices are also "recession state variables" along the lines of Cochrane (2005, Ch.9).

A positive speculative demand for commodities is consistent with Greer (2000), Gorton and Rouwenhorst (2006) and Erb and Harvey (2006), who argue that commodity futures provide large diversification benefits when added to a portfolio consisting of stocks and bonds alone. In fact, Irwin and Sanders (2011) assert that this evidence was an important factor in promoting commodity-index related products to institutional investors. Going forward, however, a positive speculative investment is hard to justify if index investment drives up prices too much. Results from Irwin and Sanders (2011), Stoll and Whaley (2009), and Buyuksahin and Robe (2010) question this price impact. Moreover, Appendix C derives the equilibrium conditions for $w_{Fut,spec} > 0$, which are sufficiently more Producers and sufficiently risk-averse Producers, such that their short hedging pressure still induces a positive futures risk premium.

These conditions are fairly mild and do not seem to be violated Post-CFMA. Using data from the CFTC Commitment of Traders Report from January 1986 to December 2010, Figure 2 shows that commercial hedger's (net) short positions are sufficient to cover non-commercial speculator's (net) long positions. To be precise, Panel A demonstrates that the OIW average net short position of hedgers has historically been larger than the OIW average net long position of speculators, whereas the difference is decreasing steadily since 1986. Further, Panel B demonstrates that the total short position of hedgers has always been larger than the total long position of speculators, although this difference is decreasing since 2000. In fact, using better daily data from the CFTC's private Large Trader Reporting System, Cheng et al. (2011) arrive at a similar conclusion: for the average commodity, traditional hedgers' short positions increase in lockstep with index investors' long positions over the last decade.

B Stock market risk in the commodity futures market

Table IV presents our tests of the model's implications for pricing in the commodity futures market. Proposition 2 predicts that stock market risk (defined as covariance with the tangency portfolio of stocks) is priced in the futures market Post-CFMA. Therefore, Panel A and B present average returns, Pre- and Post-CFMA respectively, for portfolio sorts on covariance with the CRSP value-weighted market portfolio (MKT) as well as the stock-based High minus Low Commodity Beta portfolio (HLCB).[11] In the last column, we sort on the average of these two covariances, which is a simple proxy for covariance with the tangency portfolio.[12] Proposition 2 also predicts that there is a hedging pressure effect in futures markets in both sub-periods, which is analyzed in Panel C. Finally, to ascertain that our results are not due

[11] HLCB is constructed from the one-dimensional sort of stocks on commodity beta (see Table II) and is long (short) an equal weighted portfolio of the top (bottom) two quintiles.

[12] Although portfolios sorted on the average covariance cannot be ranked a priori, because the risk premium for exposure to MKT and HLCB may differ (see Equation (10)), we find that the post-ranking beta with respect to each of the two factors lines up monotonically from the High to Low exposure portfolio. Consequently, the model implies that average returns line up monotonically as well.

to equal-weighting the futures returns, we also present results for the rank-based weighting scheme of Koijen et al. (2012).

Table IV about here.

Panel A demonstrates that stock market risk is not priced in the futures market pre-CFMA, which is consistent with previous work. Although there is a strong inverse relation between MKT exposure and mean futures returns, there is no relation between HLCB exposure and mean futures returns. Indeed, combining, the sort on the average of the two covariances demonstrates that a consistent pattern in returns is absent with a small and insignificant average return of 0.35% for the High minus Low portfolio (-0.04% for the rank-weighted portfolio).

Panel B demonstrates that stock market risk is priced in the futures market Post-CFMA, as hypothesized. First, average futures returns increase monotonically in MKT exposure, translating to an economically large and marginally significant High minus Low spread of 13.38%. The outperformance of High versus Low HLCB exposure futures is also large at 9.00%, but this spread is insignificant and the relation between HLCB exposure and returns is non-monotonic. Combining, the sort on the average of the two covariances presents a monotonic relation between stock market risk and mean futures return, however. Both the High minus Low spread and the rank-weighted portfolio return are economically large and significant at 14.59% and 11.78%, respectively.

Finally, Panel C demonstrates that mean futures returns are increasing in hedging pressure unconditionally. The effect is marginally significant in both sub-periods, but larger economically in the recent period. For instance, the average return for the High minus Low hedging pressure portfolio is 7.78% Pre-CFMA versus 13.43% Post-CFMA.

To conclude, futures returns are (i) increasing in stock market risk, but only Post-CFMA, and (ii) increasing in hedging pressure, in both sub-periods. This evidence is consistent with our model and increased participation of (Institutional) Investors in futures markets Post-CFMA, which integrates pricing. Indeed, the Post-CFMA spreads we observe in the futures market due to stock market risk are similar in magnitude to those observed in the stock market (see Table (II)). Consistent with this evidence, Tang and Xiong (2012) document that the correlation between individual commodities and the aggregate stock market has increased substantially recently.

C Robustness checks

Exploring the structural break Our analysis sofar sets the structural break at December 2003, consistent with the unprecedented increase in open interest in the commodity futures market around that time (see Figure 1). To test the sensitivity of our results, Table V reports the HLCB reversal (in average return and FFCM alpha) for different breakpoints from December 2000 until December 2005. A breakpoint at December 2000 implies that the effects of the CFMA are effective immediately after its passage, whereas subsequent breakpoints allow the effects to materialize gradually over time.

Table V about here.

For all breakpoints, the one-dimensional sort for stocks and industries results in a reversal between 13% and 23% in average and risk-adjusted returns, which is always statistically significant. Thus, our results are not sensitive to the exact dating of the breakpoint. Moving from 2000 to 2005, we see an inverted U-shape. For individual stocks, the largest difference in average returns is obtained when we split the sample in December 2002 (20.69%), whereas the largest difference in FFCM α is obtained when we split in December 2004 (23.00%). For industries, both spreads are largest when we split in December 2002. These results are consistent with formal structural break tests that identify a break between 2002 and 2004 for the HLCB portfolios, giving further support to choosing December 2003 as in Domanski and Heath (2007) and Tang and Xiong (2012).

A related issue is whether the composition of these portfolios is stable around the breakpoint. To this end, Table VI presents the time-series average of the diagonal elements of Markov switching matrices for the five stock portfolios sorted one-dimensionally on commodity beta for each of the five-year sub-periods in our sample. For instance, in the first column, we see that on a month-to-month basis, 95% (93%) of the stocks in the High (Low) beta portfolio do not switch. The different columns demonstrate that the average percentage of stocks that do not switch portfolios varies between 82% and 89% in the different sub-periods. Further, the unreported full Markov matrices show that stocks hardly ever move more than one portfolio at a time in any given sub-periods. Importantly, there is no substantial drop in this percentage in the sub-period 2001-2005. On the contrary, we observe a relatively high percentage of 89%, suggesting that the portfolios are stable.

Table VI about here.

In short, the stability Post-CFMA indicates that the documented reversal is not driven by changing covariances. Rather, in line with our model, the reversal is driven by changing returns. To further substantiate this finding, we fix the portfolio composition to what it is in December 2003 and compare the performance of this strategy to the strategy that updates its weights every month in Panel B of Table VI. First, we see that the returns of the two strategies are highly correlated Post-CFMA. For the one-dimensional sort of stocks (for the industry sort), the correlation between the two HLCB portfolios equals 90% (92%) from January 2004 until the onset of the crisis in June 2007, and 0.66 (0.57) until December 2010. Second, we observe similar reversals for the two strategies.

Other robustness checks We find that our results are robust in a number of other dimensions, which results are reported in the Internet Appendix. First, our results extend to alternative weighting schemes for the cross-section of commodities. Looking at the last columns in each panel of Tables II and III, we observe a significant reversal of around 14% when sorting on exposures to an EW commodity index, suggesting that our results are not solely driven by changing shares of open interest. Also, the Internet Appendix presents a significant reversal of over 16% for the (production-weighted) SP-GSCI commodity index.

Second, we find similar reversals in average and risk-adjusted returns when we control for the benchmark factors (MKT, SMB, HML and MOM) when estimating commodity betas. Third, our results extend when estimating risk premiums using OLS and GLS cross-sectional regressions with commodity beta-, size-, book-to-market- and industry-sorted portfolios as test assets. Thus, commodity exposures capture a risk factor that is separate from the traditional risk factors. Fourth, given that both commodity beta and size are persistent, transaction costs are unlikely to subsume the spreads. Indeed, we find similar results when rebalancing annually and when varying the length of the rolling window from two to ten years. Finally, our results are not driven by the recent financial crisis, as excluding it only strengthens the reversal.

4 Sectors, Industries and Inflation

This section presents a finer description of both the origin and the presence of the commodity risk premium in the stock market. In particular, we investigate (i) which commodity sectors drive our results, (ii) whether our stock market sorts mainly reflect industry effects, or are a pure stock-commodity play and (iii) whether our results are due to the change in the correlation between stock returns and inflation around the turn of the century, or indeed represent a change in the price of commodity risk.

A Commodity sectors

Table VII presents average post-ranking returns and FFCM alphas for portfolios sorted on Open Interest-weighted commodity sector indexes.[13] The evidence suggests that the reversal in the commodity risk premium is driven by the Energy and Metals and Fibers sectors. Pre-CFMA, stocks with a high exposure to these sectors underperform by 3.82% and 6.13%, respectively. Post-CFMA, these same stocks outperform by 13.57% and 5.84%, respectively.[14] The corresponding reversal is particularly large and significant for Energy at 17.40% (α_{FFCM} =17.50%), relative to a large but insignificant 11.97% (α_{FFCM} =8.18%) for Metals and Fibers. In contrast, sorting on either the Agriculture or the Livestock and Meats index does not yield a consistent pattern in returns in either sub-period.

Table VII about here.

In the Internet Appendix, we present sorts on the five largest commodities per sector to further analyze these effects. First, we find that a (marginally) significant reversal of about 15% is common to all energy commodities, although for Natural Gas the reversal is only large and significant in FFCM alpha. For Metals and Fibers, we find a particularly large reversal for Precious Metals (Gold, Silver and Platinum) of about 10%. For the remaining Industrial Metals and Fibers as well as Agriculture and Livestock and Meats commodities, the reversal is positive, but small.

[13] Similar results obtain for equal-weighted sector indexes.

[14] These returns are not a mirror image of the average return of the respective sector index Post-CFMA, which equals -2% for Energy and 16% for Metals and Fibers.

The fact that our results are driven by Energy and Precious Metals is unsurprising given that these are the largest commodities in terms of open interest. However, this result is also consistent with the model. First, a relatively large proportion of index investment is flowing into the Energy sector Post-CFMA, whereas energies are a relatively large and volatile component of inflation. Second, swings in both Energy and Precious Metals prices are likely most important for the macroeconomy. For instance, evidence in Hamilton (2008) suggests that Energy prices spike before recessions, whereas precious metals, and in particular Gold, are popular among investors as a safe haven and a hedge against inflation or currency risk. These views on Gold are challenged recently in Erb and Harvey (2013), however.

B Within-industry effects

The robustness of our main results for a one-dimensional sort of industries suggests that the reversal in the commodity risk premium can be captured using only between-industry variation in commodity betas. This subsection demonstrates that the reversal can also be captured using only within-industry variation. To this end we construct five market value-weighted stock portfolios within each industry by splitting at the quintiles of ranked commodity betas within that industry. Here, we exclude four financial industries and industry-months that contain fewer than ten stocks.

Table VIII presents average returns and FFCM alphas for the within-industry sort in a similar vein as Tables II and III.[15] In each block, the

[15] CAPM and FF3M alphas are similar but not presented to conserve space.

first five rows and columns present results for portfolios that equally weight the within-industry portfolios (i.e., within-industry group High, 2, 3, 4 or Low, where High consists of stocks whose beta is high relative to other stocks in the industry) of typically seven or eight industries that fall into the relevant group of the between-industry sort (i.e., between-industry group High, 2, 3, 4 or Low). The sixth column presents the average within-industry effect, which is a portfolio that equal-weights five between-industry groups. The sixth row presents the HLCB within-industry portfolios.

Table VIII about here.

Panel A demonstrates that low commodity beta stocks underperform high commodity beta stocks Pre-CFMA across the full spectrum of industry betas. In average returns, the underperformance within industries ranges from -6% to -3% per year, which adds up to a strictly monotonic commodity beta-return relation for the average within-industry portfolio and a significant HLCB spread of -4.35%. These conclusions are even stronger in risk-adjusted returns.

In Panel B we demonstrate that the Post-CFMA reversal is present across the full spectrum of industry betas, as well. The outperformance of high commodity beta stocks within each industry is monotonic and adds up to significant 11.69% for the average within-industry portfolio and again extends to risk adjusted returns. Further, in Panel C we show that this reversal is economically large and significant in four out of five between-industry groups.

In summary, these within-industry effects suggest that variation in commodity beta within industries, perhaps due to differences in corporate hedging practices, market power or the place of a firm in the supply chain, is priced in a manner consistent with our hypothesis. This indicates that our findings are not merely picking up the fundamental commodity exposure of a given industry. Rather, there are important differences in firm exposures to commodity risk within industry, even when the industry at large is not exposed.

C Inflation

One natural question is whether sorting on commodity returns is tantamount to sorting on (unexpected) inflation and therefore whether the results are driven by the reversal in the correlation between inflation and the stock market after the turn of the century (see e.g., Bekaert and Wang (2010) and Campbell et al. (2013)). To verify that the commodity effect we document is separate, we consider sorts wherein we first orthogonalize stock returns from inflation effects. Thus, in each rolling window, we run two regressions to find $\beta_{i,t-1}$

$$\begin{aligned} r_{i,s} &= a_{i,t-1} + c_{i,t-1} I_s + e_{i,s} \\ e_{i,s} &= \alpha_{i,t-1} + \beta_{i,t-1} R_{OIW,s} + \varepsilon_{i,s}, \text{ for } s = t-60, ..., t-1, \end{aligned} \tag{24}$$

where I_s is either unexpected inflation (UI) or a mimicking portfolio of unexpected inflation (UIF), which addresses the concern that stock's exposures to non-traded factors are typically small and hard to estimate. For the non-traded measure of inflation UI, we follow e.g., Erb and Harvey (2006) and Hong and Yogo (2012) and use the month t change in the annual inflation rate, i.e., $UI_t = \frac{CPI_t}{CPI_{t-12}} - \frac{CPI_{t-1}}{CPI_{t-13}}$, which assumes annual inflation is integrated of order one.[16] The inflation factor UIF is constructed using a three-by-two sort on betas with respect to UI and size, similar to Fama and French (1993).

In Table IX we present means and FFCM alphas for the usual one- and two-dimensional sorts on these inflation-controlled commodity betas for both sub-periods of interest in Panels A and B. We test the difference in Panel C. Note, the left block of results orthogonalizes returns from non-traded unexpected inflation UI, the right block from the traded unexpected inflation factor UI1F.

Table IX about here.

When controlling for UI, we see that both mean and risk-adjusted returns remain economically large and significant in both sub-periods, adding up to a HLCB spread in average returns of -7.36% (-5.14%) for the one-dimensional sort on stocks (industries) in the first sub-period and 9.74% (10.12%) in the second sub-period. The performance differentials add up to a difference of around 15% for both stocks and industries in case of both the OIW and the EW index, which is very similar to what we found in Table II. Again, these performance differentials are typically significant, strengthen in risk-adjusted returns and are strongest among the biggest stocks.

This result may not come as a surprise, given that one may not expect the commodity beta to change much when stocks' exposures to non-traded inflation are small. Indeed, we find that commodity

[16]Our results extend using three alternative measures of (unexpected) inflation used by others in the past: (i) the difference between the monthly inflation rate and the short-term t-bill rate; (ii) an ARIMA(0,1,1)-innovation extracted from the monthly inflation series; and, (iii) monthly inflation itself.

betas are by and large similar with and without UI. However, the right panel documents that the reversal in the commodity risk premium easily extends when controlling for UIF as well. Although in the first sub-period the HLCB spreads are slightly smaller, we see that they remain economically large and significant in risk-adjusted returns. Post-CFMA the HLCB spreads are very similar, adding up to a difference of over 14%, which is only slightly smaller than what we had before.

5 Conclusion

Because many investment, production and consumption decisions are conditioned on commodity prices, one would expect them to be an important risk factor. In this paper, we use the surge in institutional index investment in commodity futures markets as a quasi-natural experiment and study how commodity risk is priced before and after. We develop a model where investors are exposed to commodity price risk, but are not allowed to hedge their exposure in the futures markets initially, which is consistent with the narrow position limits set by the CFTC for this class of traders historically. In this model, commodity risk is priced in the stock market. Conversely, stock market risk is priced in the commodity futures market, but only after investor's position limits are lifted by the introduction of the CFMA.

Indeed, we find a strong pattern in average stock returns existing along the cross-section of commodity exposures. Pre-CFMA, High commodity beta stocks underperform by -8% per year in average and risk-adjusted returns, whereas Post-CFMA, these same stocks outperform by 11% per year. This reversal is consistent with the structural break in the behavior of investors who were seeking commodity exposure in the stock market Pre-CFMA and subsequently in the commodity futures market. This finding is also consistent with the fact that stock market risk only shows up in the cross-section of commodity futures returns Post-CFMA.

Our findings are particularly relevant for stocks that are strongly exposed to commodity price risk and suggest that commodity betas can be used in devising strategies that use stocks to hedge or speculate on commodity prices. This finding is particularly important for those institutions that might still be prevented or restricted, in any way, from directly investing in commodity markets. Interestingly, the performance differentials we document extend to strategies that use only between-industry variation in commodity betas and to strategies that use only within-industry variation, which implies that commodity risk can be hedged while holding industry exposures constant.

Appendix: Derivations

This appendix presents detailed derivations for the model outlined in Section 1.

A Optimal portfolio for investors with and without position limits

The first order conditions for an Investor that faces the position limit in the futures market is

$$\mu_r - \gamma_I \left\{ \Sigma_{rr} w_r + \Sigma_{rS} \varphi \right\} = 0, \tag{1}$$

from which we get:

$$w_r = \gamma_I^{-1}\Sigma_{rr}^{-1}\mu_r - \varphi\Sigma_{rr}^{-1}\Sigma_{rS}. \tag{2}$$

Similarly, without position limits, the first order conditions are

$$\begin{pmatrix} \mu_r \\ \mu_{Fut} \end{pmatrix} - \gamma_I \left\{ \begin{pmatrix} \Sigma_{rr} & \Sigma_{rF} \\ \Sigma_{Fr} & \sigma_{FF} \end{pmatrix} \begin{pmatrix} w_r \\ w_{Fut} \end{pmatrix} + \begin{pmatrix} \Sigma_{rS} \\ \sigma_{FS} \end{pmatrix} \varphi \right\} = 0. \tag{3}$$

Using that the partitioned inverse of Σ can be written as

$$\Sigma^{-1} = \begin{pmatrix} \Sigma_{rr}^{-1} + \sigma_{ee}^{-1}bb' & -\sigma_{ee}^{-1}b \\ -\sigma_{ee}^{-1}b' & \sigma_{ee}^{-1} \end{pmatrix}, \tag{4}$$

where b and $\sigma_{ee} = Var(e_{t+1})$ follow from the regression

$$R_{Fut,t+1} = a + b'r_{t+1} + e_{t+1}, \tag{5}$$

the first order conditions can be solved for w as

$$w = \begin{pmatrix} w_r \\ w_{Fut} \end{pmatrix} = \gamma_I^{-1} \begin{pmatrix} \Sigma_{rr}^{-1}\mu_r \\ \sigma_{ee}^{-1}a \end{pmatrix} - \begin{pmatrix} \gamma_I^{-1}\sigma_{ee}^{-1}a\Sigma_{rr}^{-1}\Sigma_{rS} \\ \varphi \end{pmatrix}. \tag{6}$$

Because only Investors participate in the stock market, the optimal demand for stocks w_r is the market portfolio w_m, both with and without position limits. Consequently, equilibrium expected excess stock returns are given by a two-factor asset pricing model in both cases. For each stock k we have

$$\text{With limit:} \qquad E(r_{k,t+1}) = \gamma_I \sigma_{km} + \gamma_I \varphi \sigma_{kS} \tag{7}$$

$$\text{Without limit:} \qquad E(r_{k,t+1}) = \gamma_I \sigma_{km} + \gamma_I w_{Fut,spec} \sigma_{kS}, \tag{8}$$

or in the more familiar form in terms of betas to and expected returns of the market portfolio ($r_{m,t+1}$) and a hedge portfolio for commodity price risk ($r_{h,t+1}$, with $w_m = \left(\iota_K' \Sigma_{rr}^{-1} \Sigma_{rS}\right)^{-1} \Sigma_{rr}^{-1} \Sigma_{rS}$)

$$E(r_{k,t+1}) = \beta_{km} E(r_{m,t+1}) + \beta_{ih} E(r_{h,t+1}). \tag{9}$$

B Optimal futures demand

Total output for each Producer equals $q_{t+1} = Q_{t+1}/N_P$, with expected value $\overline{q} = 1$, such that we can write $q_{t+1} R_{S,t+1} = \frac{Q_{t+1}}{N_P} g\left(Q_{t+1}\right)$. Using a Taylor series approximation of Q_{t+1} around its mean $\overline{Q}$, each Producer maximizes:

$$\max_h \frac{\overline{Q}}{N_P} g(\overline{Q}) + \frac{1}{N_P} (\overline{Q} g'(\overline{Q}) + g(\overline{Q}))(Q_{t+1} - \overline{Q}) + h r_{Fut,t+1}. \tag{10}$$

By Taylor approximation we also have $\sigma_{FS} = Cov(R_{Fut,t+1}, R_{S,t+1}) = g'(\overline{Q}) Cov(Q_{t+1} - \overline{Q}, R_{Fut,t+1})$. Focusing on the components related to h alone, this allows us to write the maximization problem as

$$\max_h h \mu_{Fut} - \frac{\gamma}{2} (h^2 \sigma_{FF} + 2h(1 + \eta) \sigma_{FS}) \tag{11}$$

where $\eta = \frac{g(\overline{Q})}{\overline{Q}g'(\overline{Q}}$ is a demand elasticity. The optimal futures demand h follows immediately from the first order condition

$$\mu_{Fut} - \gamma h \sigma_{FF} - \gamma(1+\eta)\sigma_{FS} = 0. \tag{12}$$

C Futures risk premium

Using $\lambda_i = N_i/\gamma_i$ for $i = P, S, I$, the futures risk premium in the case with limit follows directly from the market clearing condition and optimal futures demand of Producers and Speculators:

$$N_P \frac{\mu_{Fut}}{\gamma_P \sigma_{FF}} - N_P (1+\eta) \frac{\sigma_{FS}}{\sigma_{FF}} + N_S \frac{\mu_{Fut}}{\gamma_P \sigma_{FF}} = 0. \tag{13}$$

Without limit, we combine the optimal futures demand of Producers, Speculators and Investors. Using the assumption $\sigma_{FF} = \sigma_{SS} = \sigma_{FS}$, rewriting from the from the auxiliary regression in Equation (3): $a = \mu_{Fut} - \Sigma'_{rF}\Sigma_{rr}^{-1}\mu_r = \mu_{Fut} - \gamma_I \sigma_{FT}$ with $w_{Tan} = \gamma_I^{-1}\Sigma_{rr}^{-1}\mu_r$, and finally imposing futures market clearing $N_P h + N_S s + N_I w_{Fut} = 0$, we have for the expected futures risk premium

$$\begin{aligned} 0 &= \lambda_P \frac{\mu_{Fut}}{\sigma_{FF}} - \lambda_P \gamma_P (1+\eta) \qquad (14) \\ &\quad + \lambda_S \frac{\mu_{Fut}}{\sigma_{FF}} + \lambda_I (\frac{\mu_{Fut} - \gamma_I \sigma_{FT}}{\sigma_{ee}}) - \lambda_I \gamma_I \varphi \text{ such that} \\ \mu_{Fut} &= \frac{\lambda_P \gamma_P (1+\eta) + \lambda_I \gamma_I \varphi}{(\lambda_P + \lambda_S + \lambda_I \frac{\sigma_{FF}}{\sigma_{ee}})} \sigma_{FF} + \frac{\lambda_I \frac{\sigma_{FF}}{\sigma_{ee}} \gamma_I}{(\lambda_P + \lambda_S + \lambda_I \frac{\sigma_{FF}}{\sigma_{ee}})} \sigma_{FT}. \qquad (15) \end{aligned}$$

Moreover, note that market clearing implies that in equilibrium we have for the speculative demand for the futures contract by Investors

$w_{Fut,spec} = \gamma_I^{-1}\sigma_{ee}^{-1}a$:

$$
\begin{aligned}
0 &= \lambda_P \frac{\mu_{Fut}}{\sigma_{FF}} - \lambda_P \gamma_P (1+\eta) \qquad (16) \\
&\quad + \lambda_S \frac{\mu_{Fut}}{\sigma_{FF}} + N_I w_{Fut,spec} - \lambda_I \gamma_I \varphi \text{ such that} \\
w_{Fut,spec} &= \left(\frac{N_P}{N_I}(1+\eta) + \varphi \right) - \frac{(\lambda_P + \lambda_S)}{N_I} \frac{\mu_{Fut}}{\sigma_{FF}}. \qquad (17)
\end{aligned}
$$

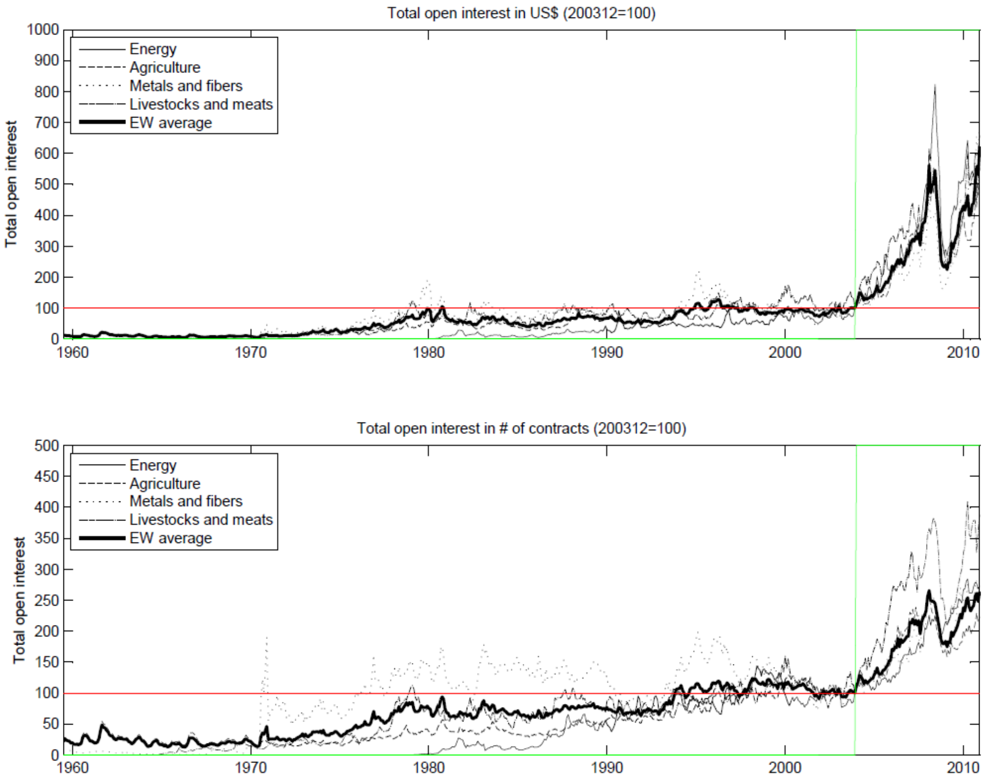

Figure 1: Total Open Interest in 33 commodities (1959 to 2010)
The top figure displays total open interest in 33 commodities in US$, which is calculated as the sum of the US$ open interest in each commodity (number of contracts outstanding times nearest-to-maturity futures price). The bottom figure displays total open interest in terms of the number of contracts outstanding. Both series are normalized to equal 100 in December 2003.

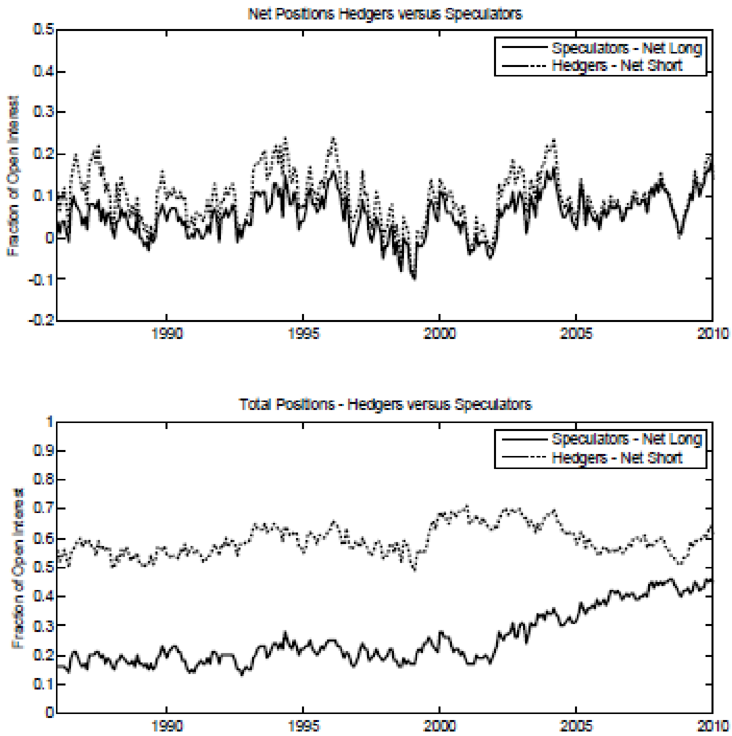

Figure 2: OIW Positions of Hedgers versus Speculators (1986-2010)
The top figure displays the Open Interest Weighted average over all commodities in the CFTC's historical Commitment of Traders (COT) reports of the net short position (short minus long) of commercial hedgers versus the net long position (long minus short) of non-commercial speculators. The bottom figure displays the Open Interest Weighted average of the short position of commercial hedgers versus the long position (long plus spreading) of non-commercial speculators. All series are presented as a fraction of Open Interest. Traders are classified as in the COT reports, which are available from 1986 onward.

Table I: Overview of commodity futures

This table presents detailed characteristics of 33 commodity futures, divided over four sectors: Energy (E), Agriculture (A), Metals and Fibers (M) and Livestock and Meats (L). The table lists: (i) a commodities' sector (sec.) and symbol (sym.; as it appears in the CRB data); (ii) the exchange on which it is traded [(1)]; (iii) the delivery months considered; (iv) the first month in which both a return and total open interest (TOI) are observed (the end date, December 2010, is common to all contracts except propane and flaxseed, for which TOI approaches zero in 2007 and 2003, respectively); (v) annualized average return and standard deviation (in US$, * indicates significance at the 10%-level); and finally, (vi) the median TOI (in US$ MM).

(Sec.) Comm. (Sym.)	Exchange	Delivery Months	First Obs.	Avg. Ret.	St. Dev.	TOI
(E) Crude Oil (CL)	NYMEX	All	198304	12.75*	33.71	7793
(E) Gasoline (HU/RB) [(2)]	NYMEX	All	198501	18.35*	35.80	2353
(E) Heating Oil (HO)	NYMEX	All	197904	9.92*	31.95	2925
(E) Natural Gas (NG)	NYMEX	All	199005	-3.74	51.79	11233
(E) Gas-Oil-Petroleum (LF)	ICE	All	198910	13.59*	32.12	2491
(E) Propane (PN)	NYMEX	All	198709	27.13*	47.05	21
(A) Coffee (KC)	ICE	3,5,7,9,12	197209	8.21	37.84	1234
(A) Rough Rice (RR)	CBOT	1,3,5,7,9,11	198701	-2.82	28.90	76
(A) Orange Juice (JO)	ICE	1,3,5,7,9,11	196703	5.50	32.75	217
(A) Sugar (SB)	ICE	3,5,7,10	196102	7.73	43.73	941
(A) Cocoa (CC)	ICE	3,5,7,9,12	195908	3.60	31.05	463
(A) Milk (DE)	CME	2,4,6,9,12	199602	2.57	24.42	531
(A) Soybean Oil (BO)	CBOT	1,3,5,7,8,9,10,12	195908	7.88*	29.85	822
(A) Soybean Meal (SM)	CBOT	1,3,5,7,8,9,10,12	195908	9.13*	29.06	1005
(A) Soybeans (S-)	CBOT	1,3,5,7,8,9,11	196501	5.69	26.98	3514
(A) Corn (C-)	CBOT	3,5,7,9,12	195908	-1.38	23.43	2083
(A) Oats (O-)	CBOT	3,5,7,9,12	195908	-0.46	29.16	51
(A) Wheat (W-)	CBOT	3,5,7,9,12	195908	0.17	24.48	833
(A) Canola (WC)	WCE	3,5,6,7,9,11	197702	0.38	22.18	196
(A) Barley (WA)	WCE	3,5,7,10,12	198906	-2.59	22.15	18
(A) Flaxseed (WF)	WCE	3,5,7,10,11,12	198501	1.27	20.26	21
(M) Cotton (CT)	ICE	3,5,7,10,12	195908	3.20	23.30	1086
(M) Gold (GC)	NYMEX	2,4,6,8,10,12	197501	1.70	19.47	6224
(M) Silver (SI)	NYMEX	3,5,7,9,12	197202	6.48	32.50	2790
(M) Copper (HG)	NYMEX	1,3,5,7,9,12	197210	10.77*	27.77	1250
(M) Lumber (LB)	CME	1,3,5,7,9,11	196911	-3.15	27.62	121
(M) Palladium (PA)	NYMEX	3,6,9,12	197702	13.26*	36.01	94
(M) Platinum (PL)	NYMEX	1,4,7,10	197208	7.69*	27.79	324
(M) Rubber (YR)	TOCOM	All	199204	9.46	32.58	565
(L) Feeder Cattle (FC)	CME	1,3,4,5,8,9,10,11	197112	3.90	16.40	516
(L) Live Cattle (LC)	CME	2,4,6,8,10,12	196412	5.46*	16.49	1925
(L) Lean Hogs (LH)	CME	2,4,6,7,8,10,12	196603	4.52	25.51	692
(L) Pork Bellies (PB)	CME	2,3,5,7,8	196402	2.03	33.72	191

[(1)] CBOT = Chicago Board of Trade; CME = Chicago Mercantile Ex.; ICE = ICE Futures US; NYMEX = New York Mercantile Ex.; TOCOM = Tokyo Commodity Ex.; WCE = Winnipeg Commodity Ex.

[(2)] Until June 2006 returns are based on the Unleaded Gasoline (HU) contract, from July 2006 on the Reformulated Gasoline Blendstock (RB) contract

Table II: Average stock returns over subsamples

This table presents average returns and standard deviations, in annualized %'s, for the commodity-beta sorted portfolios of interest. Panel A covers 1980 to 2003 (Pre-CFMA) and Panel B covers 2004 to 2010 (Post-CFMA). Panel C tests the difference between the two sub-periods. All t-statistics are based on White's heteroskedasticity-consistent standard errors.

	Panel A: Pre-CFMA						Panel B: Post-CFMA					
	OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
	Size quintile				One-way		Size quintile				One-way	
	S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
						Mean returns						
H	5.88	3.55	2.33	1.91	5.00	4.45	12.13	15.29	15.10	14.85	14.57	11.93
4	8.88	6.90	7.04	6.58	8.23	5.77	12.02	9.97	4.78	5.64	5.97	7.33
3	10.56	9.44	6.32	7.04	7.84	8.25	11.07	8.58	2.08	3.58	6.62	5.16
2	10.55	11.32	9.24	9.53	10.07	8.81	9.25	7.91	3.08	3.87	6.47	5.07
L	8.93	13.03	10.01	10.02	9.72	9.33	1.88	1.98	3.25	2.77	2.35	3.24
HLCB	-3.04	-9.47	-7.68	-8.11	-4.72	-4.88	10.25	13.31	11.85	12.08	12.22	8.69
t(HLCB)	(-1.17)	(-2.36)	(-1.77)	(-2.02)	(-1.70)	(-1.16)	(1.98)	(2.00)	(1.88)	(1.95)	(1.92)	(1.34)
						Standard deviations						
H	27.11	26.75	24.52	24.33	19.13	25.90	31.07	28.47	21.48	22.73	24.65	24.46
4	21.75	19.19	19.17	18.35	17.67	21.06	27.42	22.27	15.62	16.82	22.46	19.58
3	19.20	17.47	17.25	16.72	17.68	16.19	25.71	20.48	15.81	16.51	19.71	15.48
2	19.41	17.91	16.51	16.16	16.26	15.01	23.03	19.07	14.17	14.69	17.65	14.25
L	23.60	21.66	17.76	17.86	15.72	15.68	23.82	19.66	14.44	14.90	15.39	13.75
						Panel C: Difference						
			Returns						t-statistics			
H	6.25	11.74	12.78	12.94	9.57	7.48	(0.48)	(0.97)	(1.34)	(1.30)	(0.95)	(0.70)
4	3.14	3.06	-2.26	-0.93	-2.26	1.56	(0.28)	(0.33)	(-0.32)	(-0.13)	(-0.24)	(0.18)
3	0.51	-0.85	-4.24	-3.46	-1.22	-3.09	(0.05)	(-0.10)	(-0.61)	(-0.49)	(-0.15)	(-0.46)
2	-1.30	-3.41	-6.16	-5.66	-3.60	-3.74	(-0.14)	(-0.42)	(-0.97)	(-0.88)	(-0.48)	(-0.60)
L	-7.04	-11.04	-6.75	-7.25	-7.37	-6.09	(-0.69)	(-1.28)	(-1.03)	(-1.08)	(-1.11)	(-1.00)
HLCB	13.29	22.78	19.53	20.19	16.95	13.58	(2.29)	(2.93)	(2.55)	(2.73)	(2.44)	(1.75)

Table III: Risk-adjusted returns over subsamples
This table presents risk-adjusted returns (alphas, in annualized %'s) for the commodity-beta sorted portfolios of interest. We use the CAPM, FF3M and FFCM as benchmark asset pricing models. Panel A covers 1980 to 2003 (Pre-CFMA) and Panel B covers 2004 to 2010 (Post-CFMA). Panel C tests the difference between the two sub-periods. All t-statistics are based on White's heteroskedasticity-consistent standard errors.

	Panel A:Pre-CFMA						Panel B: Post-CFMA					
	OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
	Size quintile				One-way		Size quintile				One-way	
	S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
						α_{CAPM}						
H	-3.59	-6.71	-6.95	-7.73	-2.67	-5.86	4.40	8.32	10.30	9.45	8.61	6.07
4	0.92	-1.19	-0.72	-1.30	0.72	-3.29	5.18	4.32	0.93	1.24	0.17	2.23
3	3.49	2.13	-1.25	-0.52	0.38	0.98	4.76	3.30	-2.01	-0.77	1.46	1.07
2	3.55	3.99	2.16	2.44	3.22	2.36	3.49	3.13	-0.54	0.06	1.88	1.37
L	0.60	4.59	3.21	2.82	3.18	2.91	-3.99	-2.93	-0.08	-0.92	-1.65	-0.25
HLCB	-4.18	-11.30	-10.16	-10.54	-5.85	-8.77	8.38	11.25	10.38	10.37	10.26	6.31
t(HLCB)	(-1.63)	(-2.82)	(-2.41)	(-2.72)	(-2.11)	(-2.30)	(1.91)	(1.89)	(1.71)	(1.77)	(1.70)	(1.10)
						α_{FF3M}						
H	-3.99	-6.34	-4.36	-6.19	-4.68	-3.78	1.47	6.71	11.42	9.91	8.65	6.33
4	-1.36	-3.02	1.22	-0.11	-1.40	-0.87	2.20	2.41	1.74	1.37	-0.92	1.72
3	0.27	-0.36	0.15	0.27	-2.57	1.15	1.43	1.57	-1.88	-0.99	1.01	1.16
2	-0.21	1.25	2.42	2.18	1.45	1.54	0.68	1.51	-0.48	-0.20	1.16	1.14
L	-1.86	2.18	3.70	2.42	1.05	2.08	-6.71	-4.65	0.42	-1.02	-2.03	-0.04
HLCB	-2.13	-8.53	-8.06	-8.61	-5.73	-5.86	8.17	11.36	11.00	10.93	10.68	6.37
t(HLCB)	(-0.83)	(-2.09)	(-1.92)	(-2.25)	(-2.06)	(-1.69)	(1.96)	(1.97)	(1.84)	(1.91)	(1.89)	(1.13)
						α_{FFCM}						
H	-1.73	-6.12	-5.52	-6.67	-4.75	-3.52	1.65	6.81	11.30	9.82	8.60	6.23
4	0.69	-3.23	-0.97	-1.73	-0.92	0.40	2.40	2.46	1.67	1.33	-0.82	1.76
3	2.41	0.43	-0.61	-0.13	-1.99	0.76	1.60	1.66	-1.83	-0.93	1.08	1.16
2	2.82	3.48	3.22	3.33	2.13	1.08	0.77	1.53	-0.47	-0.19	1.23	1.18
L	2.75	5.59	5.88	4.99	2.12	2.77	-6.66	-4.67	0.36	-1.08	-2.01	-0.09
HLCB	-4.48	-11.71	-11.39	-11.66	-6.87	-6.30	8.31	11.48	10.94	10.90	10.60	6.32
t(HLCB)	(-1.91)	(-2.85)	(-2.75)	(-3.10)	(-2.44)	(-1.80)	(2.02)	(1.98)	(1.82)	(1.90)	(1.90)	(1.12)
						Panel C: Difference						
	Alphas						t-statistics					
HLCB	12.57	22.55	20.54	20.92	16.11	15.09	(2.47)	(3.14)	(2.78)	(2.98)	(2.43)	(2.18)
HLCB	10.31	19.89	19.05	19.54	16.41	12.23	(2.10)	(2.82)	(2.60)	(2.84)	(2.60)	(1.85)
HLCB	12.79	23.19	22.33	22.56	17.47	12.61	(2.70)	(3.27)	(3.06)	(3.28)	(2.79)	(1.90)

Table IV: Sorting commodity futures on stock market risk and hedging pressure

This table presents average returns (and White's heteroskedasticity consistent t-statistics in parentheses) for one-dimensional sorts of commodity futures on stock market risk (Panel A and B) and hedging pressure (Panel C). Consistent with the model of Section I, stock market risk is measured as covariance with the CRSP VW MKT portfolio (σ_{lM}) and the High minus Low Commodity Beta portfolio from a one-dimensional sort of stocks (σ_{lH}). In the last column, we present results for the average of the two (cross-sectionally standardized) covariances. The main portfolios of interest are the High minus Low spreading portfolio constructed from this sort and the rank-weighted portfolio of Koijen et al. (2013), where the weight on futures contract l, $w_{l,t}$, equals $q_t\left(rank_{l,t} - \frac{L_t}{2}\right)$ and q_t is a scalar that ensures the portfolio is long and short one unit. Panel A covers 1980 to 2003 (Pre-CFMA) and Panel B covers 2004 to 2010 (Post-CFMA). The hedging pressure sorts in Panel C cover the full sample as well as the sub-periods, but the sample runs from 1986 to 2010 dictated by data availability.

Sorting on	MKT exposure: σ_{lM}		HLCB exposure: σ_{lH}		Average exposure	
	Panel A: Stock market risk Pre-CFMA					
High	-4.60	(-1.47)	3.72	(0.77)	1.39	(0.31)
2	-1.26	(-0.42)	-2.07	(-0.74)	-0.63	(-0.24)
3	2.52	(0.85)	-0.07	(-0.02)	0.57	(0.20)
Low	5.64	(1.86)	0.66	(0.26)	1.04	(0.40)
High - Low	-10.24	(-2.65)	3.06	(0.58)	0.35	(0.07)
Rank-weighted	-7.62	(-2.27)	2.20	(0.49)	-0.04	(-0.01)
	Panel B: Stock market risk Post-CFMA					
High	13.35	(1.70)	8.02	(0.78)	15.45	(1.72)
2	7.95	(0.99)	14.74	(1.99)	6.99	(0.84)
3	6.59	(0.85)	6.54	(0.85)	4.29	(0.54)
Low	-0.02	(0.00)	-0.98	(-0.19)	0.87	(0.18)
High - Low	13.38	(1.80)	9.00	(0.93)	14.59	(1.85)
Rank-weighted	9.37	(1.49)	7.42	(0.94)	11.78	(1.83)
	Panel C: Hedging Pressure					
	Full sample		Pre-CFMA		Post-CFMA	
High	8.93	(2.67)	5.85	(1.73)	16.42	(2.06)
2	7.34	(2.22)	6.35	(1.96)	9.74	(1.19)
3	2.52	(0.74)	4.67	(1.40)	-2.72	(-0.33)
Low	-0.50	(-0.18)	-1.93	(-0.63)	2.98	(0.50)
High - Low	9.43	(2.59)	7.78	(1.92)	13.43	(1.75)
Rank-weighted	7.92	(2.61)	4.98	(1.47)	15.06	(2.37)

Table V: Exploring the structural break

This table tests the difference between the two sub-periods for alternative break-points after the introduction of the Commodity Futures Modernization Act, i.e., December 2000, 2001, 2002, 2003, 2004 and 2005. We report average returns and FFCM alphas for the HLCB portfolios. All t-statistics are based on White's heteroskedasticity-consistent standard errors.

		Difference in alternative breakpoints around CFMA											
		Alphas in ann.%'s						t-statistics					
							Dec. 2000						
Means	HLCB	9.18	12.63	14.49	15.72	15.38	9.44	(1.84)	(1.73)	(2.01)	(2.33)	(2.63)	(1.27)
FFCM	HLCB	8.93	15.18	17.92	18.31	15.59	9.79	(2.06)	(2.17)	(2.47)	(2.76)	(2.80)	(1.58)
							Dec. 2001						
Means	HLCB	8.65	14.81	19.77	19.00	15.29	10.30	(1.68)	(2.02)	(2.76)	(2.81)	(2.50)	(1.42)
FFCM	HLCB	8.92	17.79	21.60	20.75	15.18	8.22	(2.04)	(2.49)	(3.03)	(3.15)	(2.69)	(1.32)
							Dec. 2002						
Means	HLCB	13.38	18.60	21.31	20.69	18.89	15.76	(2.51)	(2.53)	(2.89)	(2.95)	(2.92)	(2.17)
FFCM	HLCB	11.90	18.65	23.40	22.21	18.03	12.32	(2.70)	(2.75)	(3.31)	(3.38)	(3.06)	(1.97)
							Dec. 2003						
Means	HLCB	13.29	22.78	19.53	20.19	16.95	13.58	(2.29)	(2.93)	(2.55)	(2.73)	(2.44)	(1.75)
FFCM	HLCB	12.79	23.19	22.33	22.56	17.47	12.61	(2.70)	(3.27)	(3.06)	(3.28)	(2.79)	(1.90)
							Dec. 2004						
Means	HLCB	12.56	22.19	20.13	20.48	17.15	15.85	(1.94)	(2.59)	(2.42)	(2.52)	(2.20)	(1.90)
FFCM	HLCB	12.24	22.63	23.17	23.00	18.14	15.83	(2.36)	(2.95)	(2.93)	(3.06)	(2.61)	(2.20)
							Dec. 2005						
Means	HLCB	10.91	22.19	15.11	16.97	13.60	13.40	(1.47)	(2.29)	(1.68)	(1.89)	(1.55)	(1.43)
FFCM	HLCB	9.51	21.29	18.32	19.37	14.15	13.34	(1.65)	(2.52)	(2.17)	(2.36)	(1.84)	(1.64)

Table VI: Stability of sort Post-CFMA

This table presents two results that demonstrate that our portfolios are stable after the introduction of the CFMA. Panel A presents a summary of Markov switching matrices for the five one-dimensionally sorted stock portfolios (from H to L) for five-year sub-periods. Each column represents the diagonal of the switching matrix (averaged over all months in the sub-period), which represents the fraction of stocks that does not switch out of that respective portfolio. Panel B presents means and FFCM alphas for stock and industry portfolios sorted one-dimensionally in five commodity beta groups, where we fix the ranking on its December 2003 value. Note, the stock portfolios contain only those stocks that are in the December 2003 sample. We present average returns and FFCM alphas for the long-only portfolios and for the high minus low commodity beta (HLCB) portfolios we also present the corresponding t-statistics based on White's heteroskedasticity-consistent standard errors. Also, we present two correlations of these portfolios with the original portfolios (that allow the composition to change freely Post-CFMA): $Corr(r_{free}, r_{fixed})$. This correlation is presented for the period until June 2007, just before the financial crisis, and until December 2010.

Panel A: Diagonal of Markov switching matrices

	1980-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010
H	0.95	0.93	0.95	0.92	0.94	0.94
4	0.87	0.83	0.87	0.79	0.86	0.83
3	0.84	0.79	0.84	0.75	0.84	0.79
2	0.85	0.82	0.87	0.77	0.87	0.81
L	0.93	0.92	0.94	0.89	0.95	0.92
Average	0.89	0.86	0.89	0.82	0.89	0.86

Panel B: Returns when portfolio composition is fixed at December 2003

	Stocks		48 Ind.	
	Means	FFCM	Means	FFCM
H	9.98	5.71	12.20	7.61
4	4.74	1.43	8.78	3.34
3	3.13	-0.74	1.76	-3.79
2	5.93	0.87	7.67	1.79
L	2.88	-2.20	4.87	-1.45
HLCB	7.10	7.91	7.33	9.06
t-stat	1.55	1.67	1.41	1.97
	June 2007	December 2010	June 2007	December 2010
$Corr(r_{free}, r_{fixed})$	0.90	0.66	0.92	0.57

Table VII: Portfolios sorted on commodity sector indexes

This table presents means and FFCM alphas for stock portfolios sorted one-dimensionally in five groups on betas with respect to Open Interest-weighted commodity sector indexes, that is, an index of six energy commodities (Energy), an index of 15 agriculture commodities (Agriculture), an index of eight metals and fiber commodities (Metals & Fibers) and an index of four livestock and meat commodities (Livestock & Meats). For the spreading portfolios (HLCB), the table also presents corresponding t-statistics based on White's heteroskedasticity-consistent standard errors in parentheses.

		Energy	**Agriculture**	**Metals & Fibers**	**Livestock & Meats**
			Panel A: Pre-CFMA		
Mean	H	4.71	8.34	4.59	6.79
	2	7.96	6.53	6.01	9.48
	3	9.09	9.13	7.64	7.65
	4	8.25	7.44	8.62	7.23
	L	8.54	7.43	10.72	5.93
	HLCB	-3.82	0.92	-6.13	0.86
	t-stat	(-0.86)	(0.29)	(-1.46)	(0.28)
FFCM α	H	-3.65	0.77	-0.92	-1.75
	2	-0.01	-0.04	-0.90	1.14
	3	1.50	1.75	1.26	-0.35
	4	1.32	0.73	1.88	1.14
	L	1.05	3.24	3.46	0.19
	HLCB	-4.69	-2.46	-4.38	-1.94
	t-stat	(-1.02)	(-0.80)	(-1.20)	(-0.58)
			Panel B: Post-CFMA		
Mean	H	14.84	4.91	8.67	11.63
	2	6.40	6.59	5.76	5.21
	3	3.54	5.41	6.61	4.46
	4	3.81	8.17	4.95	4.19
	L	1.26	3.80	2.83	5.51
	HLCB	13.57	1.11	5.84	6.13
	t-stat	(2.22)	(0.19)	(0.89)	(1.17)
FFCM α	H	9.82	-1.03	2.66	4.96
	2	2.32	1.75	1.10	-0.05
	3	-1.13	1.72	2.69	0.35
	4	-0.01	4.00	1.03	1.08
	L	-2.99	-0.62	-1.15	1.38
	HLCB	12.81	-0.41	3.81	3.58
	t-stat	(2.19)	(-0.08)	(0.68)	(0.96)
			Panel C: Difference for HLCB portfolio		
Mean	HLCB	17.40	0.20	11.97	5.26
	t-stat	(2.30)	(0.03)	(1.54)	(0.87)
FFCM α	HLCB	17.50	2.05	8.18	5.52
	t-stat	(2.36)	(0.35)	(1.24)	(1.11)

Table VIII: Within-industry sorted commodity beta portfolios
This table demonstrates the results from the within-industry sort as explained in Section 2.C. First, we sort all stocks within each industry into five commodity beta bins (presented row-wise). Then, using the aggregate industry portfolios, we sort the industries into five bins (presented column-wise). Combining, in each 5-by-5 block, a cell presents the equal weighted average of the respective (H,2,3,4 and L) within-industry portfolios among the respective (H,2,3,4 and L) beta industries. The sixth column presents the equal weighted average over rows, that is, an average within-industry portfolio. The sixth row presents the HLCB within-industry portfolio. Panel A presents the results for the first sub-period, Panel B for the second sub-period. In each panel we present average returns and FFCM α's (in annualized %'s). To conserve space, we present corresponding t-statistics (based on White's heteroskedasticity-consistent standard errors) only for the average within-industry portfolio and the HLCB within-industry portfolios.

			Between-industry group						
			H	4	3	2	L	Avg	t-stat
			Panel A: Pre-CFMA						
Mean	Within-industry group	H	3.39	4.06	4.53	7.87	7.72	5.52	(1.30)
		4	5.51	4.84	6.84	12.93	9.81	7.99	(2.22)
		3	4.25	7.58	7.66	10.59	11.02	8.22	(2.47)
		2	5.98	8.60	10.97	13.42	8.53	9.50	(2.84)
		L	6.78	10.19	8.71	11.21	12.44	9.86	(2.71)
		HLCB	-3.39	-6.13	-4.17	-3.34	-4.72	-4.35	(-2.13)
		t-stat	(-1.02)	(-1.96)	(-1.54)	(-1.14)	(-1.62)	(-2.13)	
FFCM α	Within-industry group	H	-8.27	-6.09	-5.75	-2.46	-2.23	-4.96	(-3.62)
		4	-3.97	-4.64	-3.35	4.22	0.80	-1.39	(-1.24)
		3	-5.71	-1.76	-2.09	2.64	3.57	-0.67	(-0.55)
		2	-2.81	0.54	2.05	5.12	1.58	1.30	(1.09)
		L	-1.36	1.49	-1.38	2.40	6.78	1.58	(1.09)
		HLCB	-6.92	-7.58	-4.37	-4.86	-9.01	-6.55	(-3.40)
		t-stat	(-1.84)	(-2.62)	(-1.56)	(-1.68)	(-3.19)	(-3.40)	
			Panel B: Post-CFMA						
			H	4	3	2	L	Avg	t-stat
Mean	Within-industry group	H	18.91	15.32	13.10	18.52	9.95	15.16	(1.41)
		4	17.54	6.05	8.95	7.12	11.31	10.20	(1.20)
		3	15.16	9.80	7.57	4.50	6.92	8.79	(1.26)
		2	10.40	7.47	4.14	4.36	4.90	6.25	(0.94)
		L	5.27	4.31	7.72	-0.53	0.58	3.47	(0.50)
		HLCB	13.64	11.01	5.38	19.05	9.37	11.69	(1.98)
		t-stat	(1.67)	(1.68)	(0.70)	(2.24)	(1.29)	(1.98)	
FFCM α	Within-industry group	H	12.60	6.54	3.90	7.64	1.59	6.45	(1.99)
		4	10.22	-1.71	2.52	-0.95	3.98	2.81	(1.70)
		3	8.31	3.68	2.27	-1.25	2.21	3.04	(2.12)
		2	4.39	1.29	-1.27	-1.01	0.20	0.72	(0.54)
		L	-1.33	-3.22	1.73	-6.95	-3.90	-2.73	(-1.48)
		HLCB	13.92	9.76	2.17	14.58	5.48	9.18	(2.14)
		t-stat	(1.83)	(1.60)	(0.40)	(2.54)	(1.08)	(2.14)	
			Panel C: Difference for HLCB within-industry portfolios						
Mean		HLCB	17.03	17.14	9.55	22.39	14.08	16.04	
		t-stat	(1.94)	(2.36)	(1.18)	(2.49)	(1.80)	(2.57)	
FFCM α		HLCB	20.84	17.34	6.53	19.44	14.49	15.73	
		t-stat	(2.45)	(2.57)	(1.06)	(3.02)	(2.50)	(3.35)	

Table IX: Commodity beta sorts orthogonal to (unexpected) inflation

This table presents average and risk-adjusted returns (FFCM α's) for sorts where inflation effects are netted out. In each 60-month rolling window, we first orthogonalize returns from a measure of unexpected inflation (UI, the monthly change in annual inflation; presented in the left panel) or an unexpected inflation factor (UIF, constructed from a three-by-two sort on inflation beta and Size; presented in the right panel). Then, we regress the residuals from this regression on the OIW commodity index to estimate commodity betas, which we then use to sort. Panel A covers 1980 to 2003, Panel B covers 2004 to 2010 and Panel C tests the differences for the HLCB portfolios. * indicates significance at the 10%-level, using White standard errors.

		Returns orthogonalized from unexpected inflation						Returns orthogonalized from unexpected inflation factor					
		OIW	OIW	OIW	OIW	OIW	EW	OIW	OIW	OIW	OIW	OIW	EW
		Size quintile				One-way		Size quintile				One-way	
		S	3	B	Stocks	48 Ind.	Stocks	S	3	B	Stocks	48 Ind.	Stocks
Panel A: (Risk-adjusted) Returns Pre-CFMA													
Means	H	6.20	3.90	1.99	2.31	4.67	4.28	6.79	4.73	3.87	3.38	6.05	5.88
	4	9.30*	7.12*	7.82*	7.09*	8.40*	6.42	8.76*	7.27*	6.78*	6.75*	8.17*	7.12
	3	10.17*	8.79*	6.07*	6.81*	8.65*	7.59*	10.43*	9.91*	6.26*	7.05*	7.97*	6.75*
	2	10.28*	11.95*	8.61*	8.98*	9.38*	8.82*	11.01*	10.94*	8.66*	8.91*	9.44*	8.34*
	L	9.02*	12.72*	9.77*	9.67*	9.81*	9.19*	7.88*	12.17*	8.18*	8.72*	9.35*	9.07*
	HLCB	-2.83	-8.82*	-7.78*	-7.36*	-5.14*	-4.92	-1.09	-7.44*	-4.31	-5.34	-3.30	-3.18
FFCM	H	-1.91	-5.89*	-5.88*	-6.36*	-5.19*	-3.65	-1.23	-4.46*	-4.49	-5.39*	-3.81*	-2.18
	4	1.00	-3.18*	-0.50	-1.64	-1.27	0.63	0.44	-3.26*	-1.43	-2.05*	-1.30	1.34
	3	2.23	-0.02	-0.64	-0.18	-1.00	-0.15	2.50	0.48	-0.41	0.02	-0.55	-0.58
	2	2.44	4.27*	2.90*	3.08*	1.69	1.19	3.35*	2.63*	2.31*	2.36*	0.38	0.44
	L	3.36	5.52*	5.64*	4.77*	2.41	2.93*	2.15	6.07*	3.81*	3.89*	2.11	2.55*
	HLCB	-5.27*	-11.41*	-11.53*	-11.13*	-7.61*	-6.59*	-3.38*	-10.54*	-8.30*	-9.28*	-5.92*	-4.73
Panel B: (Risk-adjusted) Returns Post-CFMA													
Means	H	12.49	12.46	13.11	12.68	12.77	11.20	13.36	14.69	13.65*	13.87	14.31	13.68
	4	10.15	9.65	3.12	4.97	6.73	7.80	11.89	9.93	5.41	6.55	3.09	6.43
	3	9.22	10.16	3.25	4.62	6.62	5.51	7.48	8.61	2.17	3.33	10.62	4.60
	2	8.66	6.16	2.07	2.78	7.03	4.99	9.25	6.26	2.06	2.86	5.06	5.06
	L	5.03	4.12	2.45	2.94	2.65	2.68	3.44	4.00	3.61	3.22	3.28	1.13
	HLCB	7.47	8.34	10.65*	9.74	10.12	8.52	9.92*	10.69	10.04*	10.65*	11.03*	12.54*
FFCM	H	2.02	4.21	9.46*	7.85*	6.46	5.32	2.81	6.53	9.89*	8.82*	7.91*	7.95*
	4	0.56	2.19	-0.15	0.59	0.05	2.62	2.20	2.48	1.99	2.02	-2.99	1.00
	3	0.03	3.22*	-0.74	0.04	1.11	1.31	-1.20	1.91	-1.32	-0.78	5.06*	0.48
	2	-0.05	-0.32	-1.35	-1.17	1.94	1.36	0.61	-0.57	-1.33	-1.06	-0.52	1.44
	L	-3.54	-2.60	-0.33	-0.81	-1.70	-0.65	-5.35*	-2.80	-0.05	-1.57	-1.05	-3.02
	HLCB	5.56	6.81	9.79*	8.66	8.16	5.97	8.16*	9.33	9.94*	10.39*	8.96	10.98*
Panel C: Difference (Post-CFMA)-(Pre-CFMA)													
Means	HLCB	10.29*	17.16*	18.44*	17.10*	15.26*	13.44*	11.01*	18.13*	14.34*	15.99*	14.33*	15.73*
FFCM	HLCB	10.83*	18.22*	21.32*	19.79*	15.77*	12.55*	11.54*	19.87*	18.24*	19.67*	14.88*	15.70*

II Sorting out the time-varying inflation risk premium

Abstract

This paper finds that the inflation risk premium (IRP) in the stock market has reversed over time. In both portfolio sorts and cross-sectional regressions, the unconditional IRP is marginally negative, but masks a reversal from a significant -8.0% in the sixties to an insignificant 5.5% in recent years. We identify the proximate causes of this time-variation and develop an asset pricing model with time-varying inflation risk to explain these dynamics. First, the reversal is driven by the growing market for TIPS since their introduction in 1997, which are the preferred hedge for inflation risk. Second, the IRP and the effect of TIPS are larger in recessions, consistent with time-varying risk aversion. Finally, a pronounced upward shift in the nominal-real covariance at the end of the 90s has also contributed to the reversal in isolation, but our evidence favors TIPS as the most important driver.

Inflation is an important risk factor for investors, consumers, and producers alike, because it threatens the real value of investments, erodes purchasing power, and redistributes wealth unexpectedly. Therefore, a natural question is whether this macroeconomic risk is priced.[1] We follow Ang et al. (2012) and sort all US stocks monthly on inflation risk, measured as beta with respect to $ARMA$-innovations in inflation. We are the first to uncover a reversal in the inflation risk premium (IRP) in the stock market, from a significant -8.0% per annum in the sixties to an insignificant 5.5% per annum in recent years. Consistent with previous work, however, we estimate an unconditional IRP that is only marginally negative.[2]

In this paper, we identify the proximate causes of this time-variation and develop an asset pricing model with time-varying inflation risk to explain these dynamics. We find that, first and foremost, the reversal in the IRP is driven by the increasing market share of Treasury Inflation-Protected Securities (TIPS) since their introduction in 1997. We argue that this result is due to the fact that TIPS allow investors to hedge inflation more adequately than the cross-section of stocks. Second, the IRP and the effect of TIPS are larger in recessions, consistent with time-varying risk aversion. These dynamics are robust and obtain in cross-sectional regressions when we (i) add an inflation mimicking portfolio to either of the traditional portfolio return-based

[1] Early theoretical work on the pricing of inflation risk includes, for instance, Roll (1973), Long (1974), Friend et al. (1976) and Elton et al. (1983). Previous empirical work on the pricing of inflation risk in the stock market, includes, for instance, Chen et al. (1986), Ferson and Harvey (1991), Boudoukh et al. (1994) and Ang et al. (2012).

[2] Chen et al. (1986) and Ferson and Harvey (1991) estimate a negative IRP among a small set of stock portfolios. Consistent with the fact that bonds are negative inflation beta assets, Buraschi and Jiltsov (2005), Ang et al. (2008), Gurkaynak et al. (2007) and D'Amico et al. (2008) estimate a positive IRP in the bond market.

asset pricing models, (ii) add the non-traded inflation innovations instead, (iii) use either portfolios or individual stocks as test assets, and (iv) control for characteristics.[3]

Finally, in isolation, the IRP is also predictable by various proxies of the nominal-real covariance, i.e., the relation between inflation and macroeconomic activity, which extends evidence from the bond market in Campbell et al. (2013). In a joint model, the contribution of the nominal-real covariance is not easily disentangled from TIPS, because TIPS were introduced around the same time the proxies experienced a pronounced upward shift at the end of the nineties. Our evidence favors TIPS as the driving force behind the reversal, however.

In our theoretical framework, inflation may enter the investor's portfolio optimization for a number of reasons. For instance, inflation is an exogenous risk for many investors, including pension funds and insurance companies with real liabilities and individuals with nominal wages. Also, inflation is relevant as a state variable for future consumption-investment opportunties in an Intertemporal CAPM along the lines of Cochrane (2005, Ch.9), as inflation forecasts negative changes in macroeconomic activity on average (Bekaert and Wang (2010) and Campbell et al. (2013)).

Historically, investors exposed to inflation risk are forced to hedge partly in the stock market, because real bonds are not available and nominal bonds are negatively exposed to inflation. We present empirical evidence that inflation beta-sorted stock portfolios are indeed an

[3] The benchmark asset pricing models are the CAPM (Sharpe (1964), Lintner (1965) and Mossin (1966)), the Fama-French three-factor model (Fama and French (1993)), and the Fama-French-Carhart model (Carhart (1997)). Although unreported, our conclusions are unchanged when adding the liquidity factor of Pastor and Stambaugh (2003).

useful component of the investor's optimal hedge portfolio for inflation risk. Because inflation is typically bad news, this finding is consistent with the observed outperformance of low inflation beta stocks. Since 1997, however, TIPS are the most important component of the inflation hedge portfolio. Accordingly, TIPS market size has grown dramatically from $30 billion at the end of 1997 to $800 billion in 2011. In turn, this growth has spurred the development of inflation derivative contracts, which could satisfy more complex inflation–linked hedging demands as well (Bekaert and Wang (2010)).

Assuming TIPS are a perfect hedge, the model indicates a zero IRP Post-TIPS, if TIPS are used to hedge exclusively. If TIPS are sufficiently attractive from a diversification (speculative) point of view, however, the model indicates a reversal in the IRP. Indeed, the incentive to hedge this speculative demand for TIPS will then dominate in the stock market. Previous literature suggests a reasonable lower-bound for the diversification benefits of TIPS is zero, consistent with our reversal to an insignificant positive risk premium in recent years.[4]

Time-varying risk aversion allows the model to fit the business cycle variation we document. In recessions, risk aversion is large, which increases the incentive to hedge the negative exposure Pre-TIPS and the non-negative exposure Post-TIPS. Further, the model suggests a possible channel through which the investor's fundamental exposure to inflation risk may vary over time, that is whether inflation shocks represent good or bad news about future macroeconomic activity. For instance, Bekaert and Wang (2010) and Campbell et al. (2013) find

[4] See, for instance, Roll (2004), Khotari and Shanken (2004), Mamun and Visaltanachoti (2006), Briere and Signori (2009), Fleckenstein et al. (2013) and Campbell et al. (2009).

that this nominal-real covariance has in fact reversed around the turn of the century, thus contributing to the reversal in the IRP.

Our model is derived under the assumption of integrated markets. Consequently, in the model, the inflation risk premium in the stock market is consistent with expected TIPS returns. Preliminary empirical evidence using the short sample of noisy TIPS returns suggests that pricing is indeed increasingly consistent between the two markets as the TIPS market grows and matures.

Our main contribution is in establishing that the IRP in the stock market is time-varying and has reversed sign around the turn of the century. Duarte and Blomberger (2012) also note this reversal, but do not investigate its proximate causes, as their focus is on the question of why inflation betas vary cross-sectionally. Campbell et al. (2013) find that term premiums in the nominal bond market have also changed sign around the turn of the century and ascribe this change to a reversal in the nominal-real covariance, proxied by the stock market beta of the long-term nominal bond. We extend this evidence to the stock market, using also the time-varying relation between inflation and industrial production or consumption growth to proxy for the nominal-real covariance.

In conclusion, however, our results suggest that the introduction of TIPS is the most important driver of the reversal of the IRP in the stock market. Thus, we argue that changing hedging preferences are an important channel through which an expansion of the menu of assets can impact risk premiums in the stock market. This argument is reminiscent of the diversification-channel through which emerging market risk premiums are varying over time with the level of integration of these markets in the world stock market (see Bekaert and Harvey (2000) and De Jong and De Roon (2005)). Finally, the business cycle variation we document confirms early, albeit weak, evidence in Chen et al. (1986) and Ferson and Harvey (1991) and is consistent with countercyclical variation in the market risk premium.[5]

A second contribution is in establishing that stocks can be an important component of an inflation hedge portfolio. Traditional studies focus on the time series of aggregate stock and bond returns and find that these standard asset classes are poor hedges against inflation, especially at short horizons (see, e.g., Fama (1981), Schotman and Schweitzer (2000) and Bekaert and Wang (2010)). We find that portfolios of individual stocks, which exploit heterogeneity in inflation betas, hedge more adequately. This finding obtains even though inflation betas are hard-to-estimate and vary substantially over time, as shown in Ang et al. (2012).

In the next section we derive an asset pricing model with inflation risk and present the main testable implications. Section B presents the methods used to estimate inflation exposures and the IRP. Section C presents the cross-section of inflation beta-sorted portfolios. Section D presents the first tests of a time-varying IRP. Section E presents unconditional and conditional cross-sectional regressions. Section F asks which assets are the best hedges against inflation risk over our sample period. Section G analyzes the role of the nominal-real covariance. Section H concludes.

[5]See, e.g., Shiller (1984); Campbell and Shiller (1988); Fama and French (1989); Ferson and Harvey (1991); Campbell and Cochrane (1999); Lettau and Ludvigson (2001).

A Model and empirical content

We derive an asset pricing model with inflation risk that indicates a time-varying inflation risk premium in the stock market. The Appendix presents the full model in detail. In this section, we only highlight the main testable implications and their empirical content. In its basic form, the model is conceptually similar to Fama (1996). In its extended form, we introduce a hedge asset to model the introduction of TIPS, which yields a rich set of new predictions.

A A CAPM with inflation risks

Consider a general one period mean-variance Markowitz (1959) problem for risk-averse agents faced with inflation risk. Denote the 'return' on the risk factor π_{t+1}, and denote each agent j's predetermined exposure as a fraction of wealth $X_{j,t}$: $q_{j,t}$. Thus, the total return on agent j's portfolio, with investments in risky assets $w_{j,t}^{A\prime}$, equals

$$R_{j,t+1}^{p} = R_t^f + w_{j,t}^{A\prime} r_{t+1}^{A} + q_{j,t}\pi_{t+1}, \tag{1}$$

where $r_{n,t+1}^{A} = R_{n,t+1}^{A} - R_t^f$, the excess return on each of N risky assets, with expected return vector $\mu_{A,t}$ and covariance matrix Σ_{AA}, respectively.[6]

Most of the time and for most investors the exposure $q_{j,t}$ is negative, consistent with three non-exclusive interpretations.[7] First, inflation is an exogenous risk that hurts, for instance, pension funds and insur-

[6] Throughout, we work with the version of the model in which only risk premia vary over time but not the covariances. The testable implications and main empirical findings are unchanged using time-varying (co-) variances.

[7] In fact, a negative exposure is also generally implied by the anxiety consumers expressed about inflation in the survey of Shiller (1996).

ance companies with real liabilities or individuals with nominal wages. Second, inflation is relevant as a state variable in an Intertemporal-CAPM along the lines of Cochrane (2005, Ch. 9), because it predicts real activity and consumption growth with a negative sign (Bekaert and Wang (2010), Duarte (2011) and Campbell et al. (2013)).[8] Finally, for investors that desire to maximize mean-variance utility over real returns, the portfolio problem is approximated by setting $q_{j,t} = -1$. In the former two cases, it is natural to allow for time-variation in this exposure. Indexation policies of pension funds are usually conditional on funding ratios, whereas the relation between inflation and real activity is time-varying.

Assuming that the portfolio problem for every agent j only depends on the mean and variance of the portfolio return in Equation (1) and aggregating over all agents, we show in Appendix A that the wealth-weighted market portfolio combines a standard speculative demand with a minimum-variance hedge demand as in, for instance, Merton (1973) and Anderson and Danthine (1981):

$$w_{m,t}^{A} = \gamma_{m,t}^{-1}\Sigma_{AA}^{-1}\mu_{A,t} - \Sigma_{AA}^{-1}\Sigma_{A\pi}q_{m,t}. \tag{2}$$

Here, $\gamma_{m,t}$ is the wealth-weighted risk aversion; $\Sigma_{A\pi}$ is the N-vector of covariances with inflation; and, $q_{m,t}$ is the wealth-weighted exposure. With $q_{m,t} < 0$, this market portfolio implies that agents adjusts upward the demand for stocks that move in-sync with inflation to hedge.

[8] In Panel A of Table VII we replicate some of this evidence.

B Introducing a (perfect) hedge asset

Suppose there exists an additional asset that is perfectly correlated with π_{t+1}, with returns r^0_{t+1}. We only need a perfect correlation for expositional purposes. As long as the new asset is a better hedge than the available assets, the hedge demand will tilt towards the new asset, such that similar predictions obtain. We think of the hedge asset to be an inflation-linked bond. There is a wide spectrum of assets that are considered potential inflation hedges, such as nominal bonds, commodities and real estate. In theory, however, TIPS are most adequate, because both coupons and principal are indexed to realized CPI inflation (albeit with a three month lag), whereas the latter is also guaranteed in case of deflation. In Section F we verify that TIPS are a crucial component of the optimal hedge portfolio for inflation risk.

Denoting the $(N+1)$-vector of excess returns on the expanded set of assets $r^X_{t+1} = (r^0_{t+1}\ r^{A\prime}_{t+1})'$, we show in Appendix B that the total demand for assets, separated in a speculative and a hedge demand, can be written as

$$w^X_{j,t} = \begin{pmatrix} w^0_{j,t} \\ w^A_{j,t} \end{pmatrix} = \begin{pmatrix} w^0_{spec} \\ \gamma^{-1}_{j,t}\Sigma^{-1}_{AA}\mu_{A,t} - \Sigma^{-1}_{AA}\Sigma_{A\pi}w^0_{spec} \end{pmatrix} - \begin{pmatrix} q_{j,t} \\ 0_N \end{pmatrix}, \tag{3}$$

where $w^0_{spec} = \gamma^{-1}_{j,t}\sigma^{-1}_{ee}a_0$ comes from the auxiliary regression $r^0_{t+1} = a_0 + b_0' r^A_{t+1} + e_{0,t+1}$ with $Var(e_{0,t+1}) = \sigma_{ee}$.

The individual components of this demand have a natural interpretation. First, the hedge demand, $(q_{j,t}\ 0'_N)'$, focuses completely on the hedge asset, because it is perfectly correlated with the risk. Second, agents want an additional investment in the hedge asset, w^0_{spec}, if it provides an abnormal return over the risky assets. Third, the optimal demand for risky assets, $w^A_{j,t}$, adjusts the tangency portfolio with a minimum-variance hedge demand for w^0_{spec}, instead of the exposure $q_{j,t}$ in Equation (2). Thus, if the agent seeks additional exposure to the hedge asset (beyond the hedge demand $q_{j,t}$) when $a_0 > 0$, he will hedge this additional exposure among the N risky assets. This result follows directly from the speculative demand for the extended set of assets (see also Stevens (1998)). Importantly, the composition of this hedge portfolio is determined by $\Sigma^{-1}_{AA}\Sigma_{A\pi}$, as in the basic framework.

C Asset pricing with two types of investors

In this subsection, we analyze what it means for the inflation risk premium in the stock market when the fraction of investors that are able to invest in the hedge asset varies over time. We assume there are two types of investors: a fraction $\varphi_{b,t}$ $(= 1 - \varphi_{e,t})$ of investors ('basic') that is unable to invest in the hedge asset and a fraction $\varphi_{e,t}$ of investors ('extended') that is able to do so. These time-varying fractions can be motivated by noting that investors will not add a new asset to their portfolio over night. Rather the investment decision is often conditional on observing market performance and liquidity reaching a critical level. In the case of TIPS, affirmation of commitment to the program by the Treasury was particularly important. In addition, Sack and Elsasser (2004) argue that investors had a benign outlook for inflation in the late nineties, thus lowering demand for TIPS initially. Consequently, TIPS market size grew only slowly after the Treasury first auctioned \$7 billion of 10-year TIPS on January 29, 1997. After the Treasury affirmed its commitment in 2002, market size increased rapidly from \$168 billion to \$800 billion at the end of 2011.

We assume that the two investors do not differ in their exposure to the risk factor on aggregate, such that $q_{b,t} = q_{e,t} = q_{m,t}$. Using the optimal portfolios given in Equations (2) and (3) and the procedure outlined in Appendix A, we find that the wealth-weighted (market) portfolio of the N assets in r^A_{t+1} is given by

$$w_{m,t} = \gamma_{m,t}^{-1}\Sigma_{AA}^{-1}\mu_{A,t} - \gamma_{m,t}^{-1}\Sigma_{AA}^{-1}\Sigma_{A\pi}Q_t. \tag{4}$$

This portfolio adjusts the Markowitz demand with a hedge demand over the aggregate exposure $Q_t = \gamma_{m,t}((1-\varphi_{e,t})q_{m,t} + \varphi_{e,t}w^0_{spec})$. As in the basic framework, the exposure $q_{m,t}$ is hedged with the risky assets by a fraction $(1-\varphi_{e,t})$ of investors. As in the extended framework, the exposure $q_{m,t}$ is hedged with the hedge asset by a fraction $\varphi_{e,t}$ of investors. Consequently, for these investors only the speculative investment in the hedge asset (w^0_{spec}) is left to be hedged with the risky assets.

From the two-factor asset pricing model that is implied by this demand, it is easily seen that the inflation risk premium is time-varying with Q_t,

$$E_t(r^A_{n,t+1}) = \gamma_{m,t}Cov(r^A_{n,t+1}, r_{m,t+1}) + Q_tCov(r^A_{n,t+1}, \pi_{t+1}), \tag{5}$$

Appendix C shows that this two-factor model can be equivalently written in beta form:

$$E_t(r^A_{n,t+1}) = \beta_{n,m} E_t(r_{m,t+1}) + \beta_{n,H} E_t(r_{H,t+1}), \tag{6}$$

where $r_{H,t+1}$ is a return on a hedge portfolio that is long high and short low inflation beta stocks with expected excess return $E_t(r_{H,t+1})$ determined by the value of Q_t. In our empirical work, we assume that portfolio sorts and cross-sectional regressions make $r_{H,t+1}$ observable.

A note on integration The asset pricing model in Equation (6) follows from focusing on the expected returns of the initial set of N risky assets (stocks) only. We do not assume that the market for the risky asset and the hedge asset are segmented, however. In Appendix D, we derive the model that jointly prices the extended set of assets, with risk premiums for the N risky assets that are identical to Equation (6). When $\varphi_{e,t}$ approaches one, this joint model collapses to the model implied by Equation (3), which includes the market portfolio of the extended set of assets ($r_{m^X,t+1}$) and the hedge asset as priced factors:

$$E_t(r^A_{n,t+1}) = \beta_{n,m^X} E_t(r_{m^X,t+1}) + \beta_{n,0} E_t(r_{0,t+1}). \tag{7}$$

D Testable implications and empirical content

To derive the main testable implications for a time-varying inflation risk premium in the stock market, we focus on two elements of the aggregate exposure: the fraction of investors with access to the hedge asset $\varphi_{e,t}$ and the market's coefficient of relative risk aversion $\gamma_{m,t}$. This focus is motivated by the introduction of TIPS and evidence suggestive of a procyclical inflation risk premium in Chen et al. (1986)

and Ferson and Harvey (1991).[9]

Appendix E expands $Q_t = \gamma_{m,t}((1-\varphi_{e,t})q_{m,t} + \varphi_{e,t}w^0_{spec})$ around $\varphi_{e,t} = 0$ and $\gamma_{m,t} = 1$, so as to mimic the basic framework with log utility. We consider two specifications of the aggregate exposure Q_t to guide our empirical analysis, which are nested in the model

$$Q_t = \theta_0 + \theta_1\varphi_{e,t} + \theta_2\gamma_{m,t} + \theta_3(\varphi_{e,t} \times \gamma_{m,t}). \tag{8}$$

First, we focus on the role of TIPS and restrict $\theta_2 = \theta_3 = 0$. Thus, when TIPS are not available (i.e., $\varphi_{e,t} = 0$), the aggregate exposure to inflation is negative, i.e., $Q_t = \gamma_{m,t}q_{m,t} < 0$. In this setting, investors pay high prices for stocks that covary with inflation risk to hedge and therefore we predict $\theta_0 < 0$ in Equation (8). When TIPS are introduced and $\varphi_{e,t}$ increases, the inflation risk premium increases as well, provided that the diversification benefits of TIPS are not too low (Equation (48) in Appendix E). The intuition is that fewer investors are hedging $q_{m,t}$ in the stock market.

When all investors have access to TIPS ($\varphi_{e,t} = 1$), the aggrate exposure collapses to $Q_t = \gamma_{m,t}w^0_{spec}$. Now suppose that TIPS provide positive diversification benefits, i.e., $w^0_{spec} > 0$. In this setting, the inflation risk premium will reverse to being positive, because the incentive to hedge this speculative investment will dominate in the stock market. In case $w^0_{spec} = 0$, inflation risk is not priced in the stock market directly, but indirectly, through the exposure of the market portfolio to π_{t+1}. This result is clear from Equation (3), where the

[9] Albeit weak, their evidence, respectively, suggests the inflation risk premium is largest when inflation is most volatile and when the Default Spread and the Dividend Yield are large. Both coincide with recessions.

demand for stocks collapses to the tangency portfolio of stocks, thus leading to the one-factor CAPM.

Evidence in Roll (2004), Khotari and Shanken (2004), Mamun and Visaltanachoti (2006) and Briere and Signori (2009) suggests that a reasonable lower bound for the diversification benefits of TIPS is zero. Also, positive diversification benefits are consistent with Fleckenstein et al. (2013), who find that TIPS are underpriced relative to a replicating portfolio of nominal bonds and inflation swaps, and Campbell et al. (2009), who find that the stock market beta of TIPS is negative, whereas realized returns have been positive. Thus, we predict $\theta_1 > 0$ and $Q_t \geq 0$ in Equation (8), such that the inflation risk premium is non-negative Post-TIPS.

Our second specification incorporates time-variation in the market's coefficient of relative risk aversion $\gamma_{m,t}$. When TIPS are not available, the aggregate exposure to inflation is negative and decreases further with $\gamma_{m,t}$, as this strenghtens the incentive to hedge. In addition, the marginal effect of $\varphi_{e,t}$ on the inflation risk premium is increasing with $\gamma_{m,t}$, provided that w^0_{spec} is not too low (Equation (50) in Appendix E). The intuition is that when the share of investors that hedge with TIPS approaches one ($\varphi_{e,t} \to 1$), Q_t approaches $\gamma_{m,t} w^0_{spec}$. Thus, only the (non-negative) speculative investment in TIPS needs to be hedged in the stock market and the incentive to do so is increasing in risk aversion. Combining, the additional predictions for the model in Equation (8) are: $\theta_2 < 0$ and $\theta_3 > 0$.

As argued before, our model is derived under the assumption of market integration, which means that the inflation risk premium must be consistent with expected TIPS returns. This consistency is testable only when $\varphi_{e,t}$ approaches 1, however (Equation (43) in Appendix D). For this reason, we test in Section E whether the risk premium for exposure to TIPS in the stock market converges to the average realized return on TIPS towards the end of our sample.

B Methodology

This section presents our measures of inflation risk and the sorting procedure that is performed to estimate the time-varing inflation risk premium.

A Inflation risk

We measure inflation using the seasonally adjusted Consumer Price Index for All Urban Consumers (CPI) available from the Bureau of Labor Statistics. We measure risk as beta with respect to inflation innovations, because the expected component of inflation is easily hedged with nominal bonds and irrelevant for cross-sectional asset pricing. Similar to Fama and Gibbons (1984), Vassalou (2000) and Campbell and Viceira (2001), we filter the time-series of monthly inflation rates using an $ARMA(1,1)$-model ($I_t = \gamma I_{t-1} + \pi_t - \delta\pi_{t-1}$, with $\widehat{\gamma} = 0.903$ and $\widehat{\delta} = 0.580$) and use in our tests the monthly innovations denoted π_t. Our conclusions are not sensitive to the specific method of extracting the innovations.[10] Also, we ascertain below that our conclusions are robust for a truly out-of-sample exercise that uses inflation in the

[10] Similar results obtain for $ARIMA(0,1,1)$-innovations, the difference between inflation and the short-term t-bill return (following Fama and Schwert (1977) and Gorton and Rouwenhorst (2006)) and the monthly change in annual inflation (following Erb and Harvey (2006) and Hong and Yogo (2012)). These results are available upon request. We can not use survey-based measures of expected inflation, because these gauge expectations over the (semi-) annual horizon only.

real-time vintage CPI series (I_t^{rv}), as in Ang et al. (2012).[11]

To fix ideas, it is important to note that the innovations π_t represent the unexpected component of inflation as well as changes in expected inflation from the model.[12] As argued in Brennan and Xia (2002), this model is the relevant case for investors when expected inflation is not observable and must be inferred from the price level itself. This dual information is exactly why our monthly horizon is relevant. On one hand, unexpected inflation is more variable than changes in expected inflation at the monthly frequency (Nelson and Schwert (1977) and Fama and Gibbons (1984)). On the other hand, (expected) inflation is persistent, which means that if a stock hedges the innovation this month, it is also hedging inflation a number of months ahead.

B Inflation betas

We sort all ordinary common stocks traded on NYSE, AMEX and NASDAQ (excluding firms with negative book equity) on their inflation betas and form portfolios at the end of each month t. We require that stocks have at least two out of the last five years of returns available. The sample period runs from August 1964 to December 2011, which is often the focus in empirical work and coincides with the introduction of AMEX stocks in the CRSP file.

We follow Duarte (2011) and estimate betas using a weighted least-

[11] Available from http://alfred.stlouisfed.org/.

[12] Taking expectations in the $ARMA(1,1)$-model, we see that the change in expected inflation over month $t-1$ is perfectly correlated to the innovation π_{t-1}:

$$E_{t-1}(I_t) - E_{t-2}(I_t) = [\gamma I_{t-1} - \delta\pi_{t-1}] - [\gamma E_{t-2}(I_{t-1})] =$$

$$[\gamma(\gamma I_{t-2} + \pi_{t-1} - \delta\pi_{t-2}) - \delta\pi_{t-1}] - [\gamma(\gamma I_{t-2} - \delta\pi_{t-2})] = (\gamma - \delta)\pi_{t-1}$$

(see also Fama and Gibbons (1984)).

squares regression over all observations in the interval $[1:t]$.[13] The expanding window ensures that we use as much information as possible, whereas exponentially decaying weights ensure timeliness of the estimated beta. Thus, for each stock i the estimator of $\beta_{i,t}$ is given by

$$\left(\widehat{\alpha_{i,t}}, \widehat{\beta_{i,t}}\right) = \underset{\alpha_{i,t},\beta_{i,t}}{\arg\min} \sum_{\tau=1}^{t} K(\tau)\left(R_{i,\tau} - RF_{\tau} - \alpha_{i,t} - \beta_{i,t}\pi_{\tau}\right)^2 \tag{9}$$

$$\text{with weights } K(\tau) = \frac{\exp(-|t-\tau|\ h)}{\sum_{\tau=1}^{t-1}\exp(-|t-\tau|\ h)}. \tag{10}$$

With $h = \frac{\log(2)}{60}$, the half-life converges to 60 months for large t. We transform the estimated $\widehat{\beta_{i,t}}$ using the Vasicek (1973) adjustment

$$\widehat{\beta_{i,t}^{v}} = \widehat{\beta_{i,t}} + \frac{var_{TS}(\widehat{\beta_{i,t}})}{\left[var_{TS}(\widehat{\beta_{i,t}}) + var_{CS}(\widehat{\beta_{i,t}})\right]}\left[mean_{CS}(\widehat{\beta_{i,t}}) - \widehat{\beta_{i,t}}\right], \tag{11}$$

where the subscripts TS and CS denote means and variances taken over the time-series and cross-sectional dimension, respectively. In this way, $\widehat{\beta_{i,t}^{v}}$ is a weighted average of the estimated beta in the time series and the cross-sectional average beta, where the former receives a larger weight when it is estimated more precisely. For instance, Elton et al. (1978) show that this adjustment makes ex-ante exposures better predictors of ex-post exposures. Indeed, we find the usual rolling window betas to be more noisy, although they provide us with largely similar evidence. Also, we ascertain below that our conclusions are robust to controlling for the benchmark factors of the CAPM (Sharpe (1964), Lintner (1965) and Mossin (1966)), the Fama-French three-factor model (Fama and French (1993), denoted FF3M), and the

[13] For the out-of-sample exercise, we omit month t as inflation is not announced until the middle of month $t+1$.

four-factor model of Carhart (1997; denoted FFCM) when estimating inflation exposures.

C Inflation risk premium

This subsection explains how we bring the model with a time-varying inflation risk premium to the data. To be consistent with extant asset pricing literature, we focus on the beta asset pricing model in Equation (6), where expected returns of the market portfolio and the hedge portfolio for inflation risk satisfy

$$\begin{pmatrix} \mu_{m,t} \\ \mu_{h,t} \end{pmatrix} = \begin{pmatrix} \sigma_M^2 & \Sigma_{MH} \\ \Sigma_{HM} & \sigma_H^2 \end{pmatrix} \begin{pmatrix} \gamma_{m,t} \\ z_{m,t} \end{pmatrix},$$

with $z_{m,t} = Q_t(\iota_N' \Sigma_{AA}^{-1} \Sigma_{A\pi})$ (Equation (32) in Appendix C). Thus, both $\mu_{m,t} = E_t(r_{m,t+1})$ and $\mu_{h,t} = E_t(r_{h,t+1})$ are time-varying as linear functions of $\gamma_{m,t}$ and Q_t. If the correlation between $r_{m,t+1}$ and $r_{h,t+1}$ is equal to zero, Q_t solely determines the expected return of the inflation hedge portfolio. If the correlation is unequal to zero or time-varying, we can still back out the linear relation between $r_{h,t+1}$ and Q_t by controlling for the market in either time-series or cross-sectional regressions.[14] Similarly, we control for the FF3M and FFCM, which additional factors can be motivated as hedge portfolios for additional risks.

[14]Note, the correlation between the aggregate stock market and inflation has changed from negative (the famous failure of the Fisher hypothesis) to positive around the turn of the century (Campbell et al. (2013)). In Section G we analyze directly how this reversal impacts the inflation risk premium.

Hedge portfolio returns We use two standard approaches to estimate returns on the inflation hedge portfolio $r_{h,t+1}$: portfolio sorts and cross-sectional regressions, which strategies have in common that they construct a zero-investment portfolio that is long in high beta stocks and short in low beta stocks. To start, we construct 30 market-value weighted portfolios that are at the intersection of a two-way sort in ten inflation beta groups and three Size groups (denoted UI1S30). Our choice for Size as control variable responds to Ang et al. (2012), who find that the best inflation hedgers are the smallest stocks. The main take-away of a time-varying inflation risk premium is robust to controlling for Book-to-Market or Momentum instead.[15] We measure Size as market cap at the end of month t and split into Micro, Small and Big stocks at the 20th and 50th NYSE percentile as in Fama and French (2008). Thus, our first estimates of the inflation risk premium are the High minus Low (HLIB) spreading portfolios derived from this two-way sort. In particular, we will focus on the Size-controlled HLIB portfolio that averages over the three Size groups.

The second set of estimates of the inflation risk premium is found by conducting cross-sectional regressions for various sets of portfolios and individual stocks. For these regressions, we construct a traded inflation factor INF. Similar to SMB and HML, we sort all CRSP stocks independently into three inflation beta groups (split at the terciles of ranked values) and two Size groups (split at NYSE median market cap). Then, the factor INF that captures the common variation in returns related to inflation betas is the average of the portfolios "low

[15] These results are available upon request.

beta, small" and "low beta, big" minus the average of the portfolios "high beta, small" and "high beta, big". In a number of robustness checks, we use the non-traded inflation innovations as risk factor instead. Finally, we also conduct cross-sectional regressions using TIPS returns as a risk factor.

We do not consider dividend yields as an alternative measure of expected returns (see, e.g., Bekaert and Harvey (2000) and De Jong and De Roon (2005)). The motivation is that dividend yields are not particularly informative about expected returns in the cross-section of inflation beta-sorted portfolios Pre- versus Post-TIPS. According to the present-value identity of Campbell and Shiller (1988), dividend yields must predict either returns or dividend growth rates or both. Cochrane (2008) finds that the evidence is in favor of return predictability for the aggregate stock market. Maio and Santa-Clara (2013), however, find that this conclusion applies only to Big and Growth stocks. Similarly, we find that high inflation beta stocks are characterized by return predictability, but low beta stocks by dividend growth predictability. Moreover, dividend growth rates differ between high and low beta stocks and this difference is strongly time-varying, which further complicates making inferences.[16]

Proxy variables This subsection describes the proxies we use to bring the unobservable model parameters $\varphi_{e,t}$ and $\gamma_{m,t}$ to the data. For $\varphi_{e,t}$ we use the relative market share of TIPS (denoted $TIPS_t$), measured as the total value of outstanding TIPS (from Barclays) over the total market value of all stocks in the CRSP file. This proxy takes into

[16] These results are available upon request.

account that institutions cannot change their investment practices overnight, whereas small investments in TIPS will likely have little effect on pricing in the stock market. For $\gamma_{m,t}$ we use the Chicago FED National Activity Index (denoted $CFNAI_t$).[17] Our choice of a business cycle indicator is consistent with countercyclical risk aversion in Campbell and Cochrane (1999) and Brandt and Wang (2003), for instance.

To sum up, we have two empirical specifications

$$r_{h,t+1} = \lambda_0 + \lambda_1 TIPS_t + u_{t+1} \text{ and} \tag{12}$$

$$r_{h,t+1} = \lambda_0 + \lambda_1 TIPS_t + \lambda_2 CFNAI_t + \lambda_3 (TIPS_t \times CFNAI_t) + u_{t+1} \tag{13}$$

Since risk aversion is countercyclical, the hypotheses developed in Section A.D translate to the predictions: $\lambda_0 < 0$, $\lambda_1 > 0$, $\lambda_2 > 0$ and $\lambda_3 < 0$. In our cross-sectional regressions, we allow the risk premiums of all factors to vary over time. The null hypothesis here is that neither $TIPS_t$ nor $TIPS_t \times CFNAI_t$ predicts, because the factor risk premiums are the returns on artifical portfolios that have no exposure to inflation risk. Time-varying risk aversion, on the other hand, may well be relevant for all factors.

C Inflation beta sorted portfolios

Table I describes the set of Inflation beta and Size-sorted portfolios. To conserve space, we present results for only four beta groups (High,

[17] Specifically, we use the 3-month moving average of the index: CFNAI-MA3, available at: http://www.chicagofed.org/webpages/publications/cfnai. Our results are similar for NBER dating, but we prefer the CFNAI because it is available in real-time (since 2001) and is known to be a good predictor of inflation.

four, seven and Low) and the HLIB spreading portfolios. We report pre- and post-ranking inflation exposures as well as annualized average return and standard deviation in Panels A to C.

Panel A demonstrates that there exist stocks across a wide spectrum of ex ante exposures ranging from -10.9 to 5.3. The post-ranking betas line up monotonically and average out to 2.9 for the Size-controlled HLIB portfolio. This exposure is significant and economically large, translating to an incremental monthly return of 73 basis points when π_t increases by one standard deviation (2.9×0.25). In contrast, the inflation beta of the aggregate stock market is -2.3, such that it loses over 50 basis points on the same occassion. Thus, we have created portfolios that are exposed to inflation risk, which implies inflation is not a useless factor in the sense of Kan and Zhang (1999) and is a necessary and sufficient condition for the portfolios to carry the risk premium. In fact, Table VI demonstrates that these HLIB portfolios are present in the optimal inflation hedge portfolio historically.

Next, we see that average returns decrease with inflation beta, but the relation is not strictly monotonic. The HLIB spreads are significant, except among Micro stocks, averageing out to -4.28% ($t = -2.12$) for the Size-controlled HLIB portfolio.[18] A negative unconditional inflation risk premium is consistent with previous estimates in Chen et al. (1986) and Ferson and Harvey (1991), in a small set of stock portfolios, and Buraschi and Jiltsov (2005), Ang et al. (2008), Gurkaynak et al. (2007) and D'Amico et al. (2008), in the bond market. The

[18] Note, this estimate is insignificant when considering the data mining-corrected t-statistic cutoffs in Harvey et al. (2013).

estimate is sensitive to the exact specification, however, and weakens when we control for the benchmark factors MKT, SMB, HML and MOM when estimating inflation betas in Panel B. This finding could be due to substantial variation over time, as hypothesized in Section A. Moreover, Ang et al. (2012) estimate an insignificant positive risk premium among individual stocks over the same sample period. The discrepancy is due to differences in the sorting methodology, because the conclusions from Panel A extend in the truly out-of-sample sort on betas with respect to I_t^{rv} in Panel C.[19] Importantly, the conditional evidence we present below is not sensitive to these differences.

Panel D reports average portfolio characteristics: Size, Book-to-market and Momentum.[20] If these characteristics explain the cross-section of expected returns completely, one would expect a positive unconditional inflation risk premium, because our strategy loads on Small, Value and Winner stocks on average. Further, one would expect the inflation risk premium to increase Post-TIPS, because in these years, the tilt towards Small and Winner stocks is stronger. In the cross-sectional regressions of Table E, we test whether the inflation risk premium is separate to these characteristics.

In the Internet Appendix we characterize these portfolios further in terms of industry composition (based on 48 industries available from Kenneth French's Web Site). In short, we find that industry composition needs to vary substantially over time to be maximally

[19] To be precise, Ang et al. (2012) (i) use 60 month rolling window betas, (ii) sort in five beta groups and (iii) do not control for Size.

[20] Size is market cap in billions of dollars. Book-to-Market (BM) is calculated in June as the ratio of the most recently available book-value of equity in Compustat (assumed to be available six months after the fiscal year-end) divided by Market Capitalization from CRSP (Size) at previous year-end. Prior return is defined as $\prod_{j=12}^{2}(1 + r_{i,t+1-j})$.

exposed to inflation (see also Ang et al. (2012)). Nevertheless, Panel B demonstrates that an industry-neutral strategy, which exploits only within-industry variation in inflation betas, is also useful as an inflation hedge.

D Time-series regressions

This section presents the first formal tests of a time-varying inflation risk premium, which hypotheses are derived in Section A and summarized in Equation (8). We regress returns of (Size-controlled) inflation beta-sorted portfolios on the relative market share of TIPS ($TIPS_t$) and the Chicago Fed National Activity Index ($CFNAI_t$). We consider three specifications and report the results in Table II. Specification (A) regresses returns on lagged $TIPS_t$, for which regression the model predicts a negative intercept λ_0 and a positive coefficient λ_1 (see Equation(12)). Specification (B) adds $CFNAI_t$ and the interaction term $TIPS_t \times CFNAI_t$, for which the model, respectively, predicts a positive coefficient λ_2 and a negative coefficient λ_3 (see Equation (13)). Model (C) adds four benchmark predictors: Dividend Yield (DY_t), Default Spread (DS_t), Risk-Free Rate (RF_t) and Term Spread (TS_t). All variables are standardized, except for $TIPS_t$, which is normalized to have standard deviation one only. This normalization ensures that the intercept measures the unconditional inflation risk premium before TIPS were introduced. For Models (B) and (C), the table presents the p-value of a Wald-test of the hypothesis that the inflation risk premium is not time-varying with $TIPS_t$, $CFNAI_t$ and $TIPS_t \times CFNAI_t$. The sample period is July 1967 to December 2011, dictated by data availability.

Let us focus initially on the HLIB portfolio in Panel A. First, the intercept λ_0 is negative and significant in each specification around -7.0%. A negative unconditional average return is consistent with our model and the idea that inflation is bad news on average. Second, λ_1 is positive and significant at 5.85 in Model (A), which suggests that $TIPS_t$ predicts HLIB portfolio returns to increase.[21] This finding is consistent with our model in that an increasing market share of TIPS, which are the preferred hedge for inflation risk, implies that fewer investors are hedging in the stock market. Thus, forcing the inflation risk premium in the stock market up from its historically negative value.

In Model (B), $TIPS_t$ is largely driven out by $CFNAI_t$ and the interaction term, which coefficients λ_2 and λ_3 are large and significant at 8.17 and -6.18, respectively. As a result, the Wald-test comfortably rejects the hypothesis of no time-variation. These coefficient estimates are consistent with the model in that risk aversion is larger in recessions, which implies for lower values of $CFNAI_t$: (i) a lower inflation risk premium Pre-TIPS and (ii) a stronger effect of increasing TIPS market share. Note also that Model (B) fits considerably better than Model (A) at an adjusted-R^2 of 4.21% relative to 1.22%, which is meaningful for a predictive regression of monthly returns. Plugging in the realized values of the independent variables in 1967 and 2011, the coefficient estimates in Model (B) imply a reversal in the inflation

[21] Note, the correlation between $TIPS_t$ and a linear (post-1997) time trend is 0.95. In results that are available upon request, we find that $TIPS_t$ predicts with the hypothesized sign even when orthogonalized from this time trend.

risk premium from a significant -11.24% to an insignificant 7.36%. A positive insignificant risk premium Post-TIPS is consistent with the model in that investors that use TIPS to hedge inflation risk, have only the speculative investment in TIPS left to hedge in the stock market. Previous literature suggests this speculative investment is non-negative.

Two additional results stand out from Panel A. First, the coefficients $\lambda_0, \lambda_1, \lambda_2$ and λ_3 vary monotonically with Inflation Beta. Second, controlling for the benchmark predictors in Model (C) leaves these conclusions unchanged. Also, these conclusions are not affected much when excluding the financial crisis. The only difference is that λ_3 halves and is only marginally significant, which is likely due to the fact that we effectively only have the recent recession to identify this coefficient.[22]

Panel B shows that the time-variation in the inflation risk premium weakens when we control for a stock's exposure to the benchmark factors when estimating inflation beta. A possible explanation is that exposures to inflation, a non-traded factor, are relatively small and hard to estimate. We analyze the relation with the benchmark factors more closely below. For now it is important to note that these models do imply a similarly significant reversal from about -6% in 1967 to 10% in 2011. Panel C demonstrates largely similar time-variation in the risk premium from the truly out-of-sample sort on I_t^{rv}. The only difference with Panel A is a slightly smaller, although marginally significant, unconditional inflation risk premium.

[22] In the Internet Appendix, we also document that an industry-neutral strategy, which exploits only within-industry variation in inflation betas, obtains similar time-varying returns, as well.

The long-horizon regressions in Panel D further stress the economic significance of these results. We annualize returns over three forecasting horizons $k = 3, 12, 24$ (standard errors are Newey - West with lag length k). First, the estimated coefficients λ_0 and λ_1 are similar to the one-month horizon. In contrast, the coefficients λ_2 and λ_3 shrink as the horizon increases, which is due to turbulent economic times (measured by the lowest $CFNAI_t$-values) being relatively short-lived. Nevertheless, the coefficients are of the hypothesized sign at all horizons, which translates to clear rejections in the Wald-test. Finally, R^2 increases monotonically in the horizon from 4.21% for $k = 1$ to 28.93% for $k = 24$ in Model (B) (see Fama and French (1988) and Campbell (2001) for similar evidence for the aggregate stock market).

In conclusion, the inflation risk premium, as measured by returns on Inflation Beta-sorted portfolios, is varying over time in the predicted fashion with the market share of TIPS and over the business cycle. In the Internet Appendix, we analyze whether this time-variation is robust to controlling for conditional exposures to the benchmark factors of the CAPM, FF3M and FFCM, similar to Ferson and Harvey (1999). We relegate this exercise to the Internet Appendix because it is not clear ex ante why betas with respect to the benchmark factors should vary over time, and, in particular, with $TIPS_t$. First, we see that the time-variation in Inflation Beta-sorted portfolio returns is not explained in unconditional factor models. Exposures to the benchmark factors are strongly varying over time, however, consistent with the portfolio characteristics reported in Table I. In case of the CAPM and FF3M, these time-varying exposures are not enough to fully explain the observed time-variation in HLIB returns. In contrast, a FFCM that conditions exposures on $TIPS_t$,$CFNAI_t$ and $TIPS_t \times CFNAI_t$ completely eradicates the time-varying inflation risk premium. We find that this supreme fit is largely mechanical. Our WLS procedure to estimate inflation betas puts the largest weight on observations close to t, such that the strategy loads on winners when inflation innovations were high recently and vice versa.[23]

The cross-sectional regressions that follow explicitly control for the relation between Inflation Beta and Momentum as well as other factors and characteristics. Thus, this exercise allows us to answer the ultimate question of whether inflation betas contain independent information for expected returns in the cross-section.

E Cross-sectional regressions

The previous section analyzed the inflation risk premium derived from the returns of Inflation Beta-sorted portfolios. We now turn to cross-sectional estimates of the inflation risk premium. Table III presents summary statistics and some predictability evidence for the benchmark factors that we use as well as the inflation factor INF. The unconditional average return of INF is insignificantly negative at -1.60%, which is small relative the benchmark factors. As before, this unconditional estimate masks important time-variation. In the full model, the intercept as well as the coefficients on $CFNAI_t$ and

[23] Two additional pieces of information are necessary to fully understand the result. First, inflation innovations are typically low in recessions, such that we load on losers. Second, a regression of MOM on $CFNAI_t$ shows that MOM returns are similar in recessions and expansions Pre-TIPS, but extremely low in the recent financial crisis, when losers outperform winners by about 1.75% per month on average.

$TIPS_t \times CFNAI_t$ are large and significant at -3.61, 5.85 and -3.51, respectively, which adds up to a reversal from a significant -6.72% in 1967 to an insignificant 5.61% in 2011. For the benchmark factors, the Wald-test of no time-variation only rejects in case of SMB, which returns are larger in recessions. Further, the R^2 of the full model stands out for Momentum at 7%, driven by a large and significant coefficient on $TIPS_t \times CFNAI_t$.

Table IV presents cross-sectional regressions where we allow risk premiums to vary over time. We consider three types of regressions. Type (A) is the standard Fama and MacBeth (1973) cross-sectional regression estimate of the unconditional risk premium (with Shanken (1992) standard errors). Type (B) and (C), respectively, condition the risk premiums on M instruments, such that $Z_t = (1, TIPS_t)$ or $Z_t = (1, TIPS_t, CFNAI_t, TIPS_t \times CFNAI_t)$. We estimate the time-varying risk premium coefficients using the pooled time-series cross-sectional regression

$$R_{i,t+1} = \lambda'(\widehat{\beta_{i,t}} \otimes Z_t) + u_{i,t+1},$$

where $\widehat{\beta_{i,t-1}}$ is a $K - vector$ of estimated factor exposures for the benchmark models and the models that add INF. λ is the $KM \times 1 - vector$ of parameters to be estimated. This pooled second stage gives identical estimates to a three-stage setup, where the second stage runs cross-sectional regressions in each month $t+1$ and the third stage runs predictive regressions of the time-series of risk premium estimates on the instruments.[24] The three-stage approach is used in Ferson and

[24] This identity extends the analysis of cross-sectional regressions in Cochrane (2005, Ch. 12) to

Harvey (1991) and Cohen et al. (2005) and is consistent under the assumption that the measurement error in the betas is uncorrelated with the instruments. The pooled regression is consistent under the same assumption and is attractive, because it provides the standard errors in one go, which we cluster on time. The first-stage betas used as independent variable in the second stage are the usual constant, full sample betas. The regressions do not include an intercept to increase efficiency, but our conclusions are robust in this dimension.

In Panel A, we use 30 Inflation Beta and Size-sorted portfolios (UI1S30) as test assets. We present the estimated risk premiums (λ), the time-series average of the second-stage cross-sectional R_t^2, a Wald-test of the hypothesis that the inflation risk premium does not vary over time and the model-implied inflation risk premium at the beginning and the end of the sample period. The remaining Panels B to E present a range of robustness checks where we omit the estimated risk premiums for the sake of brevity. These can be found in the Internet Appendix.

In short, Panel A demonstrates that exposure to inflation risk is compensated with a time-varying price that is consistent with realized returns of the inflation factor INF. First, the unconditional inflation risk premium is an insignificant -2% when INF is added to the CAPM, FF3M and FFCM. Allowing for variation with the market share of TIPS in Model (B), $\lambda_{0,INF}$ turns significant at about -4% in each model, consistent with the idea that inflation is bad news historically. In Model (B), $\lambda_{1,INF}$ is significant positive at around 3.5. Thus, as

a conditional setting.

hypothesized, when TIPS market share increases, the premium that is required from low Inflation Beta stocks decreases, because fewer investors hedge inflation risk in the stock market.

Model (C) conditions further on the state of the business cycle, which results in $TIPS_t$ being driven out by $CFNAI_t$ and $TIPS_t \times CFNAI_t$, as before. The estimated coefficients $\lambda_{2,INF}$ and $\lambda_{3,INF}$ are large and significant at 7 and -4, respectively, and imply that the inflation risk premium is largest (in absolute value) in recessions. In sum, these cross-sectional regressions imply a reversal from -8% to 5.5%, which is consistent with the model where investors hedge inflation risk in the stock market Pre-TIPS, but hedge a non-negative speculative investment in TIPS in the stock market once TIPS are introduced.

Finally, we see that adding INF improves the average cross-sectional R_t^2 considerably: from 4% to 21% in the CAPM, 36% to 44% in the FF3M and 40% to 47% in the FFCM. The unconditional risk premiums for MKT, SMB and HML are quite similar to the average realized returns of these factors. MOM is an exception, however, with a small and insignificant unconditional risk premium. In unreported results, we find that the time-variation in the SMB, HML and MOM risk premiums weakens considerably whenever INF is included, which is consistent with the idea that the set of Inflation Beta-sorted portfolios is hard-wired to attribute any "common" variation to INF.

This choice is not driving our results, however. Indeed, Panel B presents largely similar results when we expend the set of test assets with 17 industry (IND17) and 25 Size and Book-to-Market (25SBM) portfolios.[25] To show that our results are not specific to constructing the traded factor INF either, Panel C uses as measure of inflation risk the non-traded inflation innovations π_t. In this case, the implied reversals are slightly weaker in absolute value, which is likely due to larger noise in the estimated exposures.[26] Panel D shows that our conclusions also survive the test of model misspecification proposed in Berk (1995) and Jagannathan and Wang (1996), that is the inclusion of characteristics.[27]

As a final check of robustness, Panel E presents firm-level cross-sectional regressions. Here we use a three-stage setup and estimate the conditional risk premiums by regressing the second stage Fama and MacBeth (1973) estimates (that use the time-varying betas that were previously used to sort) on the instruments. We present results for two models: FF3M+π_t and FFCM+π_t, both ex- and including characteristics, which are standardized cross-sectionally.[28] Note, consistent with previous literature, the average cross-sectional R^2 among individual stocks is small compared to using portfolios.

Without characteristics, the Wald-test of no time-variation in the inflation risk premium in Model (C) rejects marginally. Further, the coefficients for the time-varying inflation risk premium have the hypothesized sign, but are less significant and imply a reversal that is scaled differently, from an insignificant -2.5% in 1967 to an insignif-

[25] Both available from Kenneth French's Web site.

[26] To calculate implied risk premiums that are comparable to Panel A and B, we scale the coefficient estimates from Panel C by the post-ranking beta of the HLIB portfolios from Panel B of Table I.

[27] These characteristics are standardized cross-sectionally at each time t. For IND17 and SBM25, Prior return is estimated using the returns on the portfolios, not the stocks inside.

[28] Note, these cross-sectional regressions are biased in favor of characteristics, which unlike betas, can be measured without error.

icant 10% in 2011.[29] This discrepancy with previous portfolio-level evidence weakens, however, when we include characteristics. In this case, the implied reversal again runs from a large and significant -5% in 1967 to a marginally significant 11% in 2011.

In the end, all specifications provide us with evidence of an inflation risk premium that varies with both the market share of TIPS and over the business cycle. In cross-sectional regressions, the inflation risk premium cannot be explained by the benchmark factors and characteristics, which suggests that inflation beta contains orthogonal information about expected returns. The exact magnitude of the implied reversal does vary across specifications, which is likely due to two problems. First, exposures to a non-traded factor are relative difficult to estimate. Second, the cross-sectional distribution of inflation exposures is varying over time. Both problems are most severe for the case of individual stocks analyzed in Panel E.

A Joint pricing of stocks and TIPS

This subsection presents preliminary evidence that the pricing of inflation risk in the stock market is consistent with the pricing of TIPS, using the available 15 years of TIPS returns. To be precise, our model suggests that the risk premium in the stock market for a unit exposure to TIPS converges to the expected return on TIPS towards the end of the sample.

In Panel A of Table V, we present cross-sectional regressions using the set of 30 Inflation Beta and Size-sorted portfolios (UI1S30) as test

[29] To calculate implied risk premiums that are comparable to the previous panels, we scale the coefficient estimates from Panel E by the average pre-ranking beta of the HLIB portfolios in 1967 and 2011, which is about 13.

assets. The asset pricing model includes the CRSP VW market portfolio and a portfolio of TIPS (an index of all maturity TIPS available from Barclays Capital) as factors.[30] To alleviate concerns about noisy TIPS prices in the market's early years, we use a 60 month rolling window to estimate betas and impute the first set of estimated betas in February 2002 for the five years before.

In short, we find that the estimated risk premium for exposure to TIPS in the stock market (λ_{TIPS}) is indeed converging to the average excess return on TIPS (r_{TIPS}), which is presented as well. In the first five-year period from 1997 to 2001, the two risk premiums differ by a large and significant 8.72% ($\lambda_{TIPS} = 10.17\%$ versus $r_{TIPS} = 1.45\%$). In the two subsequent five-year periods, the difference is small and insignificant at -0.41% and 0.11%, respectively.[31]

Another way to test this convergence is by asking whether the model with TIPS predicts a cross-section of expected returns that is similar to predictions from the original model, which includes the inflation factor INF. To this end, Panel B presents the same set of cross-sectional regressions for this original model and, in the last column, the cross-sectional correlation between expected returns for the set of 30 portfolios predicted by these two competing models.[32] Expected returns are calculated in each month t by multiplying the rolling window

[30] In contrast to what is implied by our model, our proxy of the market portfolio does not include TIPS. The motivation is that the relative market value of TIPS is small.

[31] This conclusion is largely robust to including SMB, HML and MOM and using the larger set of 72 portfolios. These results are available upon request.

[32] Note that TIPS returns are less time-varying than returns on the inflation factor INF. This finding is not inconsistent with the model. Consider Equation (39) of Appendix D, which equates supply (fixed at $w^0_{m,t}$) and demand in the TIPS market: $w^0_{m,t} = \varphi_{e,t}(w^0_{spec} - q_{m,t})$. We see that the hedge demand for TIPS (that is, $q_{m,t}$) is not likely to cause a strong upward pressure on TIPS prices through the equilibrium quantity w^0_{spec}. The reason is that the share of investors that is able to invest in TIPS ($\varphi_{e,t}$) was small when TIPS were introduced, but increases gradually over the sample period as does the supply of TIPS by the Treasury.

betas with the ex-post average factor risk premiums in each five-year period. We find that the average cross-sectional correlation is increasing from -0.03 in the first five-year period, to 0.60 and 0.65 in the two subsequent five-year periods. Although preliminary, this evidence suggests that the pricing of inflation risk in the stock market is increasingly consistent with realized TIPS returns as this market grows and matures.

F Do stock portfolios and TIPS hedge inflation risk?

This section asks whether our stock portfolios as well as TIPS are an important component of the portfolio that optimally hedges inflation risk. TIPS hedging ability is necessary for our model to have economic content, but is not a given in practice. For instance, TIPS hedging ability may be hampered by a three month indexation lag, illiquidity in the market's early years and volatile prices in the recent financial crisis. For this reason, Table VI presents regressions of $ARMA(1,1)$-innovations in inflation (Panel A) and inflation itself (Panel B) on gross returns of the one-month t-bill (TB1, from CRSP), the 10 year constant maturity treasury bond (CMT10, from CRSP), the inflation factor (INF, a zero-investment strategy) and the portfolio of TIPS.[33]

In the period before TIPS, TB1 and INF, with long positions, and CMT10, with a short position, are significant components of the optimal inflation hedge portfolio with a joint R^2 of 7.34%. Out of these three assets, INF obtains the highest R^2 in isolation at 4.07% with a

[33] Results are similar when we use the sort in ten inflation beta groups and when we substitute CMT10 with the Merrill Lynch U.S. Treasury bond Index from Datastream.

coefficient of 0.020 ($t = 3.94$).[34]

Post-TIPS, both CMT10 and INF are marginally significant in isolation, but little variation is explained at R^2's of 3.22% and 1.06%, respectively. Combining a short position in CMT10 with TIPS improves the fit considerably to an R^2 of 11.32%. In fact, only CMT10 and TIPS are significant in the joint regression with similarly large positions of -0.07 and 0.07. This combination intuitively captures an innovation in inflation, i.e., unexpected inflation plus changes in expected inflation. On one hand, TIPS compensate the investor for realized inflation. On the other hand, the investor pays expected inflation on the short position in CMT10, which asset loads negatively on changes in expected inflation.

Panel B demonstrates that these results are robust to hedging total inflation instead. Pre-TIPS, TB1 is the best hedge at an R^2 of 23.94%, which confirms Ang (2012). INF is, however, a significant component of the joint hedge portfolio that obtains an R^2 of 26.91%. Post-TIPS, TB1 and INF are driven out by the long-short combination of TIPS and CMT10, with the joint model achieving an R^2 of 11.12% relative to 0.20% for TB1 in isolation. In unreported results we find that these conclusions extend for inflation (innovations) compounded up to three months in the future, after which the hedging ability of both INF and TIPS starts to weaken.

To conclude, we find that our inflation beta-sorted stock portfolios were present in the optimal hedge portfolio for inflation risk historically. However, after the introduction of TIPS, this asset provides for

[34] The aggregate stock market achieves a similar R^2 of 4.74%. However, the required position is negative (-0.011, $t = -3.64$), consistent with the historical failure of the Fisher hypothesis.

a much better hedge when combined with a short position in nominal bonds. This finding means that substituting part of an existing position in nominal bonds, which have a negative exposure to inflation, with TIPS is desirable for many institutions. In terms of our model, such reallocation implies that investors can unwind their hedge positions in the stock market post-1997, which leads to the documented reversal in the inflation risk premium.

G The inflation risk premium and the nominal-real covariance

So far we have focused on TIPS to explain the reversal in the inflation risk premium. Now, we ask whether a time-varying nominal-real covariance has also contributed to this reversal. This question is motivated by a reversal in the relation between inflation and future macroeconomic activity, the nominal-real covariance, towards the end of the nineties. In related work, Campbell et al. (2013) use this nominal-real covariance as a state variable that governs time-variation in nominal bond returns and estimate a consequent reversal in term premia over the recent decade.

Panel A of Table VII summarizes the evidence for a reversal in the nominal-real covariance. We regress inflation (from $t-2$ to $t-1$) on future (log) industrial production growth and (log) non-durables and services consumption growth. We denote the coefficients b^1_{IP} and b^1_{CG}, when using the growth rate from t to $t{+}1$, and b^{12}_{IP} and b^{12}_{CG}, for twelve month cumulative growth rates from t to $t+12$. For comparison to Campbell et al. (2013), we also present the negative of the stock market beta of the 10 year constant maturity government bond bond (b_B^1). In short, we see that over the second half of the last decade inflation largely predicts negative changes in macroeconomic activity, whereas in the recent decade inflation predicts positive changes. Indeed, both inflation and real activity were low in the recent crisis.

A Testable implications, empirical content and proxy variables

In the model of Section A, the investor's fundamental exposure to inflation $q_{m,t}$ can be motivated by noting that inflation is a state variable for consumption-investment opportunities in an Intertemporal CAPM along the lines of Cochrane (2005, Ch. 9), Vassalou (2003) and Koijen et al. (2013), for instance. Indeed, inflation shocks can be either good or bad news for investors, depending on how inflation predicts macroeconomic activity.

To set the stage, we go back to the model outlined in Section A and consider the second-order Taylor expansion using one additional element of the aggregate exposure: the market's exposure to inflation risk $q_{m,t}$. Starting from $Q_t = \gamma_{m,t}((1-\varphi_{e,t})q_{m,t} + \varphi_{e,t}w^0_{spec})$, Appendix F derives the following extended model for the aggregate exposure

$$\begin{aligned} Q_t &= \theta_0 + \theta_1\varphi_{e,t} + \theta_2\gamma_{m,t} + \theta_3(\varphi_{e,t}\times\gamma_{m,t}) + \\ &\quad \theta_4 q_{m,t} + \theta_5(q_{m,t}\times\gamma_{m,t}) + \theta_6(\varphi_{e,t}\times\gamma_{m,t}), \end{aligned} \tag{14}$$

where we predict $\theta_4 > 0, \theta_5 > 0$ and $\theta_6 < 0$, in addition to $\theta_0 < 0$, $\theta_1 > 0$, $\theta_2 < 0$ and $\theta_3 > 0$, which were derived before.

First, the inflation risk premium increases with $q_{m,t}$. The intuition is that when a shock to inflation contains less adverse news about macroeconomic activity, the investor's incentive to hedge weakens and the inflation risk premium will adjust accordingly. Second, the marginal effect of $q_{m,t}$ is increasing with $\gamma_{m,t}$, when the investor's incentive to hedge is larger. Finally, the marginal effect of $q_{m,t}$ is decreasing with $\varphi_{e,t}$. For if all investors hedge using TIPS, no one is hedging the exposure $q_{m,t}$ in the stock market.

We follow a simple, but flexible approach and use backward-looking estimates of the relation between inflation and real activity, consumption or stock returns to proxy for $q_{m,t}$. These running estimates are obtained by running the regressions in Panel A of VII using historical data only in each month t. The specification is similar to the inflation betas of Equation (9): using an expanding window and Weighted Least Squares.[35] Thus, we regress returns (or twelve month ahead compounded returns) of the inflation factor INF on the running measures $b^1_{IP,t}$, $b^1_{CG,t}$ and $b^1_{B,t}$ (or $b^{12}_{IP,t}$, $b^{12}_{CG,t}$ and $b^1_{B,t}$) and the control variables:

$$\begin{aligned} r_{INF,t+1} &= \lambda_0 + \lambda_1 TIPS_t + \lambda_2 CFNAI_t + \lambda_3 (TIPS_t \times CFNAI_t) + \quad (15) \\ &\quad \lambda_4 b_{IP,t} + \lambda_5 (b^1_{IP,t} \times CFNAI_t) + \lambda_6 (b^1_{IP,t} \times TIPS_t) + u_{t+1}, \end{aligned}$$

where the additional hypotheses are $\lambda_4 > 0$, $\lambda_5 < 0$ and $\lambda_6 < 0$.

B Empirical evidence

In Panel B of Table VII we consider three versions of Equation (15). Model (A) focuses on the nominal real-covariance and restricts $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_5 = \lambda_6 = 0$. Model (B) allows for business cycle variation

[35] The expanding window starts in February 1959, dictated by consumption data availability. The WLS procedure uses an exponential weighting scheme with a half-life of 60 months.

and restricts $\lambda_1 = \lambda_3 = \lambda_6 = 0$. Model (C) is the full specification for which we also present a Wald test of the hypothesis that the nominal-real covariance does not add anything to the model analyzed in previous sections, i.e., $\lambda_4 = \lambda_5 = \lambda_6 = 0$.

In short, we see that our proxies of the nominal-real covariance, which are all standardized, predict largely with the right sign unless we control for $TIPS_t$. Focusing on the first proxy $b_{IP,t}$, we see that λ_4 is significant at 3.73 in Model (A). In Model (B), both $b^1_{IP,t}$ and its interaction with $CFNAI_t$ are significant with the hypothesized sign ($\lambda_4 > 0$ and $\lambda_5 < 0$). These findings are consistent with the model and suggest that as the systematic economic news contained in inflation shocks becomes more adverse, the risk premium decreases and particularly so in recessions. Intuitively, in this scenario, high inflation beta stocks become more attractive as a hedge and therefore have higher prices (lower expected returns), which effect is particularly strong when risk aversion is large. In Model (C) all coefficients related to $b_{IP,t}$ turn insignificant, however, and the Wald-test cannot reject. In contrast, both $CFNAI_t$ and $TIPS_t \times CFNAI_t$ are similarly large and significant to Table III.

For twelve month compounded returns, λ_4 and λ_5 become more significant in Model (A) and (B). This is consistent with idea that the nominal-real covariance captures a slow-moving component of the inflation risk premium. This is also clear from the R^2's, which are much larger at 18% versus 3% in Model (B), for instance. However, again, the Wald-test cannot reject the hypothesis that the nominal-real covariance is superfluous in Model (C). Indeed, results for the alternative proxies $b_{CG,t}$ and $b_{B,t}$ are by and large similar.

In summary, we find that the inflation risk premium is predictable with various proxies of the nominal-real covariance, which extends the bond market evidence in Campbell et al. (2013). Our evidence suggests, however, that the nominal-real covariance has little to add to a model that already includes the market share of TIPS. A possible explanation for the difficulty in disentangling the two effects follows from observing that (i) the Post-TIPS sample is short and (ii) the admittedly noisy proxies of the nominal-real covariance have seen a very pronounced upward shift that roughly coincides with the introduction of TIPS in 1997.[36] Indeed, Panel C shows that bIP_t^1 predicts with a large coefficient only in the Post-TIPS period.

H Conclusion

This paper follows a long tradition of papers at the intersection of macroeconomics and asset pricing and finds that there exists an inflation risk premium (IRP) in the cross-section of US stocks that reverses from -8.0% in the sixties to an insignificant 5.5% in recent years. We uncover three forces that guide this time-variation. First and foremost important for the reversal is that the IRP is increasing in the market share of TIPS. Second, the IRP and the effect of TIPS are larger in recessions, consistent with time-varying risk aversion. Finally, a time-varying nominal-real covariance contributes to the reversing IRP in isolation. This predictability is largely driven out by TIPS, however, which could be due to the fact that our noisy proxies of the nominal-

[36] In the time-series the correlation between various measures of the nominal-real covariance and $TIPS_t$ is about 0.70.

real covariance experience a pronounced upward shift around the same time TIPS were introduced.

We derive a simple asset pricing model to motivate the reversal. Inflation may enter the model as an exogenous risk or as a state variable. In either case, it is natural to assume that inflation is typically bad news for the average investor. Historically, real bonds are not available and nominal bonds are exposed with a negative sign. Consequently, high inflation beta stocks are attractive as a hedge, such that a negative IRP obtains Pre-TIPS. Since 1997, however, TIPS allow the investor to hedge inflation more adequately, leaving only the speculative investment in TIPS to be hedged in the stock market. Previous literature suggests that this investment is non-negative, in which case our model indicates that the IRP reverses.

An alternative explanation for the reversal focuses on the role of inflation as a state variable, with inflation shocks predicting negative changes in macroeconomic activity until the end of the nineties. In contrast, inflation shocks predict positive changes over the recent decade, such that inflation is not necessarily bad news anymore. Our evidence surely favors the market share of TIPS as driving factor of the reversal, however.

A number of extensions come to mind. First, a thorough investigation of the nominal-real covariance, and the independent information this variable contains for the IRP in the stock market, may benefit from directly modelling the stochastic discount factor in the economy, as in Campbell et al. (2013). Relatedly, Campbell et al. (2009) note that the nominal-real covariance may well change sign again, which could present an ideal opportunity to test our model out-of-sample. Furthermore, we leave open the question of why firm's inflation exposures differ in the cross-section, which is analyzed in Duarte and Blomberger (2012). Finally, because we have a short sample of TIPS returns, our evidence is only suggestive that the pricing of inflation risk in the stock market is consistent with TIPS.

Appendix: Derivations

A Basic framework

This section presents a detailed derivation of the basic framework of the model outlined in Section A.A. Defining as $\mu_{\pi,t}$ and σ_π^2 the expected 'return' and variance of the risk factor, respectively, the expected return and variance of agent j's portfolio can be written as

$$E_t(R_{j,t+1}^p) = R^f + w_{j,t}^{A\prime}\mu_{A,t} + q_{j,t}'\mu_{\pi,t} \text{ and} \tag{16}$$

$$Var_t(R_{j,t+1}^p) = w_{j,t}^{A\prime}\Sigma_{AA}w_{j,t}^A + q_{j,t}'\sigma_\pi^2 q_{j,t} + 2w_{j,t}^A\Sigma_{A\pi}q_{j,t}, \tag{17}$$

where $\Sigma_{A\pi}$ is the $N \times 1$ covariance matrix of the risky assets and the risk factor. Although we assume constant covariances the model can be extended to incorporate time-varying (co-) variances.

With the assumption that the portfolio problem of the agent depends only on the mean and variance of portfolio returns, the problem that agent j (with risk-aversion $\gamma_{j,t}$) has to solve is, using obvious notation,

$$\max_{w_{j,t}^A} \; E_t(R_{j,t+1}^p) - \frac{\gamma_{j,t}}{2}Var_t(R_{j,t+1}^p). \tag{18}$$

Plugging in equations (16) and (17) we obtain the following first-order condition for each agent j

$$\mu_{A,t} = \gamma_{j,t}\Sigma_{AA}w^A_{j,t} + \gamma_j\Sigma_{A\pi}q_{j,t}. \tag{19}$$

Aggregating over all agents $j = 1, ..., J$, weighting by their relative wealth $x_{j,t} = X_{j,t}/\sum_{j=1}^{J} X_{j,t}$, and rewriting we get

$$\begin{aligned}
\sum_{j=1}^{J} x_{j,t}\gamma_{j,t}^{-1}\mu_{A,t} &= \sum_{j=1}^{J} x_{j,t}\begin{pmatrix} \Sigma_{AA} & \Sigma_{A\pi} \end{pmatrix}\begin{pmatrix} w^A_{j,t} \\ q_{j,t} \end{pmatrix} \text{ such that} && (20)\\
\mu_{A,t} &= \gamma_{m,t}\begin{pmatrix} \Sigma_{AA} & \Sigma_{A\pi} \end{pmatrix}\begin{pmatrix} w^A_{m,t} \\ q_{m,t} \end{pmatrix} \Leftrightarrow && (21)\\
w^A_{m,t} &= \gamma_{m,t}^{-1}\Sigma_{AA}^{-1}\mu_{A,t} - \Sigma_{AA}^{-1}\Sigma_{A\pi}q_{m,t}. && (22)
\end{aligned}$$

where $\gamma_{m,t}^{-1}$, $w^A_{m,t}$ and $q_{m,t}$ are the wealth-weighted risk tolerance, investments in risky assets, and exposure to the risk factor, respectively, of the market m. This demand is easily rearranged to a standard two-factor asset pricing model

$$E_t(r^A_{n,t+1}) = \gamma_{m,t}Cov(r^A_{n,t+1}, r_{m,t+1}) + \gamma_{m,t}q_{m,t}Cov(r^A_{n,t+1}, \pi_{t+1}) \tag{23}$$

where both exposures to the market and inflation risk are priced.

B Extended framework

This section presents a detailed derivation of the extended framework of the model, where we introduce an asset that hedges the risk factor perfectly as described in Section A.B.

Using the same notation as before, denote the expanded set of $N+1$

assets X, such that $\mu_{X,t} = \begin{pmatrix} \mu_{0,t} \\ \mu_{A,t} \end{pmatrix}$, a $(N+1)-vector$ of expected excess returns; $\Sigma_{XX} = \begin{pmatrix} \sigma_{00} & \Sigma_{0A} \\ \Sigma_{A0} & \Sigma_{AA} \end{pmatrix}$, a $(N+1)\times(N+1)-matrix$ of (co-) variances; and, $\Sigma_{X\pi} = \begin{pmatrix} \sigma_{0\pi} \\ \Sigma_{A\pi} \end{pmatrix}$, a $(N+1)-vector$ of covariances with the risk factor. From the optimization problem in equation (18), we obtain a familiar first-order condition and optimal demand for each agent j

$$\begin{aligned} \mu_{X,t} &= \gamma_{j,t}\Sigma_{XX}w_{j,t}^{X} + \gamma_{j,t}\Sigma_{X\pi}q_{j,t} \Leftrightarrow & (24) \\ w_{j,t}^{X} &= \gamma_{j,t}^{-1}\Sigma_{XX}^{-1}\mu_{X,t} - \Sigma_{XX}^{-1}\Sigma_{X\pi}q_{j,t}. & (25) \end{aligned}$$

This Appendix serves to define the total demand, separated in a speculative and a hedge demand, in more detail. Consider the auxiliary regression $r_{t+1}^{0} = a_0 + b_0^{'}r_{t+1}^{A} + e_{0,t+1}$, which 'hedges' the risk in the new asset, r_{t+1}^{0}, with the risky assets, r_{t+1}^{A}. Thus, a_0 is the hedged expected return on the hedge asset, b_0 are the minimum-variance hedge weights, and σ_{ee} is the idiosyncratic variance of the hedge asset. From the definition of a partitioned inverse the hedge demand will equal

$$\Sigma_{XX}^{-1}\Sigma_{X\pi} = \begin{pmatrix} \sigma_{ee}^{-1} & -\sigma_{ee}^{-1}b_0^{'} \\ -\sigma_{ee}^{-1}b_0 & \Sigma_{AA}^{-1} + \sigma_{ee}^{-1}b_0b_0^{'} \end{pmatrix} \begin{pmatrix} \sigma_{0\pi} \\ \Sigma_{A\pi} \end{pmatrix} \qquad (26)$$

$$= \begin{pmatrix} \sigma_{ee}^{-1}b_0^{'}\Sigma_{A\pi} + \sigma_{ee}^{-1}\sigma_{e\pi} - \sigma_{ee}^{-1}b_0^{'}\Sigma_{A\pi} \\ -\sigma_{ee}^{-1}b_0b_0^{'}\Sigma_{A\pi} - \sigma_{ee}^{-1}b_0\sigma_{e\pi} + \Sigma_{AA}^{-1}\Sigma_{A\pi} + \sigma_{ee}^{-1}b_0b_0^{'}\Sigma_{A\pi} \end{pmatrix},$$

where the second equality follows from defining $Cov(r_{t+1}^{0}, \pi_{t+1}) =$

$b_0'\Sigma_{A\pi} + \sigma_{e\pi} = \sigma_{0\pi}$. If the asset r^0_{t+1} is indeed perfectly correlated to the risk factor π_{t+1}, we get that $\sigma_{ee}^{-1}\sigma_{e\pi} = 1$ and $b_0 = \Sigma_{AA}^{-1}\Sigma_{A\pi}$, such that the hedge demand can be written as

$$\Sigma_{XX}^{-1}\Sigma_{X\pi} = \begin{pmatrix} 1 \\ 0_N \end{pmatrix}. \tag{27}$$

An intuitive result, because with a perfect hedge asset available, agents will only use this asset to hedge.[37] Plugging this hedge demand into the total demand $w^X_{j,t} = (w^0_{j,t}\ w^{A\prime}_{j,t})'$ we get

$$\begin{aligned}
w^X_{j,t} &= \gamma_{j,t}^{-1}\begin{pmatrix} \sigma_{ee}^{-1} & -\sigma_{ee}^{-1}b_0' \\ -\sigma_{ee}^{-1}b_0 & \Sigma_{AA}^{-1} + \sigma_{ee}^{-1}b_0b_0' \end{pmatrix}\begin{pmatrix} \mu_{0,t} \\ \mu_{A,t} \end{pmatrix} - \begin{pmatrix} q_{j,t} \\ 0_N \end{pmatrix} && (28)\\
&= \begin{pmatrix} \gamma_{j,t}^{-1}\sigma_{ee}^{-1}a_0 \\ \gamma_j^{-1}\Sigma_{AA}^{-1}\mu_{A,t} - b_0\gamma_j^{-1}\sigma_{ee}^{-1}a_0 \end{pmatrix} - \begin{pmatrix} q_{j,t} \\ 0_N \end{pmatrix} && (29)\\
&= \begin{pmatrix} w^0_{spec} \\ \gamma_{j,t}^{-1}\Sigma_{AA}^{-1}\mu_{A,t} - \Sigma_{AA}^{-1}\Sigma_{A\pi}w^0_{spec} \end{pmatrix} - \begin{pmatrix} q_{j,t} \\ 0_N \end{pmatrix}, && (30)
\end{aligned}$$

where the last equality defines $w^0_{spec} = \gamma_{j,t}^{-1}\sigma_{ee}^{-1}a_0$, a Markowitz demand for the hedge asset given that it is hedged using the auxiliary regressions. Initially, we focus on the stock market and derive from this demand the expected returns for the initial set of N risky assets only. In Appendix A.4, we derive the joint pricing model for the set of $N+1$ assets.

[37] Note that the unit investment in the hedge asset can be scaled by the ratio $\frac{\sigma_\pi}{\sigma_0}$ if these standard deviations are unequal.

C A beta asset pricing model

In this section we rewrite the asset pricing model

$$E_t(r^A_{n,t+1}) = \gamma_{m,t} Cov(r^A_{n,t+1}, r_{m,t+1}) + Q_t Cov(r^A_{n,t+1}, \pi_{t+1}) \qquad (31)$$

to a beta-form, that is, in terms of betas to and expected returns of the market portfolio and a hedge portfolio as in Fama (1996). Define the scaled exposure ($z_{m,t}$) and the hedge portfolio (H) for the risk factor as

$$z_{m,t} = Q_t(\iota'_N \Sigma^{-1}_{AA} \Sigma_{A\pi}) \text{ and} \qquad (32)$$

$$H = \frac{1}{\left(\iota'_N \Sigma^{-1}_{AA} \Sigma_{A\pi}\right)} \Sigma^{-1}_{AA} \Sigma_{A\pi}, \qquad (33)$$

with $\iota'_N H = 1$, such that H is a vector of scaled regression coefficients from a regression of π_{t+1} on r^A_{t+1}, a hedge portfolio. Starting from equation (31) we have

$$\begin{aligned} \mu_{A,t} &= \gamma_{m,t} \Sigma_{Am} + \Sigma_{AA} \Sigma^{-1}_{AA} \Sigma_{A\pi} Q_t && (34) \\ &= \gamma_{m,t} \Sigma_{Am} + \Sigma_{AH} z_{m,t}. && (35) \end{aligned}$$

Using that the first-order conditions in equation (35) must also hold for the market portfolio and the hedge portfolio themselves, we get

$$\begin{pmatrix} \mu_{m,t} \\ \mu_{h,t} \end{pmatrix} = \begin{pmatrix} \sigma^2_M & \Sigma_{MH} \\ \Sigma_{HM} & \sigma^2_H \end{pmatrix} \begin{pmatrix} \gamma_{m,t} \\ z_{mt} \end{pmatrix}. \qquad (36)$$

Inverting equation (36), which solves for $\gamma_{m,t}$ and $z_{m,t}$, and substituting in equation (35) gives

$$\mu_{A,t} = \begin{pmatrix} \Sigma_{AM} & \Sigma_{AH} \end{pmatrix} \begin{pmatrix} \sigma^2_M & \Sigma_{MH} \\ \Sigma_{HM} & \sigma^2_H \end{pmatrix}^{-1} \begin{pmatrix} \mu_{m,t} \\ \mu_{h,t} \end{pmatrix} \rightarrow \tag{37}$$

$$E_t(r^A_{n,t+1}) = \beta_{n,m} E_t(r_{m,t+1}) + \beta_{n,H} E_t(r_{H,t+1}), \tag{38}$$

that is, a simple beta-APM in exposures to and expected excess returns of the market portfolio and the hedge portfolio for non-tradable inflation risk.

D A joint pricing model

In this appendix, we derive a joint pricing model for stocks and TIPS that gives expected returns for the N risky assets that are identical to Equation (6). We start by aggregating the demand for the initial set of N risky assets (stocks) and the $N+1$th hedge asset (TIPS) over the two types of investors. Naturally, for the basic investors (with wealth share $(1-\varphi_{e,t})$) the demand for the hedge asset is fixed to zero:

$$w^X_{m,t} = \begin{pmatrix} w^0_{m,t} \\ w^A_{m,t} \end{pmatrix} \tag{39}$$

$$= (1-\varphi_{e,t}) \begin{pmatrix} 0 \\ \gamma^{-1}_{m,t} \Sigma^{-1}_{AA} \mu_{A,t} - \Sigma^{-1}_{AA} \Sigma_{A\pi} q_{m,t} \end{pmatrix} \tag{40}$$

$$+\varphi_{e,t} \begin{pmatrix} w^0_{spec} - q_{m,t} \\ \gamma^{-1}_{m,t} \Sigma^{-1}_{AA} \mu_{A,t} - \Sigma^{-1}_{AA} \Sigma_{A\pi} w^0_{spec} \end{pmatrix} \tag{41}$$

$$= \begin{pmatrix} \varphi_{e,t}(w^0_{spec} - q_{m,t}) \\ w^A_T - \varphi_{e,t} \Sigma^{-1}_{AA} \Sigma_{A\pi} w^0_{spec} - (1-\varphi_{e,t}) \Sigma^{-1}_{AA} \Sigma_{A\pi} q_{m,t} \end{pmatrix} \tag{42}$$

$$= w^X_{T,t} - \left(\begin{pmatrix} q_{m,t} \\ 0_N \end{pmatrix} + (1-\varphi_{e,t})(q_{m,t} - w^0_{spec}) \begin{pmatrix} -1 \\ \Sigma^{-1}_{AA} \Sigma_{A\pi} \end{pmatrix} \right), \tag{43}$$

where $w^A_{T,t} = \gamma^{-1}_{m,t}\Sigma^{-1}_{AA}\mu_{A,t}$ and $w^X_{T,t} = \gamma^{-1}_{m,t}\Sigma^{-1}_{XX}\mu_{X,t}$, the tangency portfolio of the set of N and $N+1$ assets, respectively. This demand can be rewritten to the beta asset pricing model

$$E_t(r_{n,t+1}) = \beta_{n,m^X} E_t(r_{m^X,t+1}) + \beta_{n,H^X} E_t(r_{H^X,t+1}), \tag{44}$$

where the two priced factors are the return on the extended market portfolio $r_{m^X,t+1}$ and the return on the pseudo hedge portfolio $r_{H^X,t+1}$. The latter portfolio is not a hedge portfolio in the usual sense, because it combines the minimum-variance hedge demands for investors without and with excess to the hedge asset. Because both factors may be partly invested in the hedge asset, this model is not testable, except when $\varphi_{e,t} = 1$. In this case, the joint pricing model collapses to

$$E_t(r_{n,t+1}) = \beta_{n,m^X} E_t(r_{m^X,t+1}) + \beta_{n,0} E_t(r_{0,t+1}), \tag{45}$$

where the hedge asset itself is the second priced factor.

E Testable implications I

In this appendix we derive the main testable implications for the time-variation in the aggregate exposure Q_t driven by time-variation in $\gamma_{m,t}$ and $\varphi_{e,t}$. Start from $Q_t = f(\gamma_{m,t}, \varphi_{e,t}) = \gamma_{m,t}((1-\varphi_{e,t})q_{m,t} + \varphi_{e,t} w^0_{spec})$ and expand around the base case scenario given by the point (1, 0). Then we have

$$f(1, 0) = q_{m,t}, \tag{46}$$

which means that in the base case scenario, the inflation risk premium equals $q_{m,t}$, which is assumed to be negative. The two first order derivatives are given by

$$
\begin{aligned}
f_{\gamma_{m,t}} &= ((1-\varphi_{e,t})q_{m,t}+\varphi_{e,t}w^0_{spec}) \Leftrightarrow f_{\gamma_{m,t}}(1,0)=q_{m,t}, && (47)\\
f_{\varphi_{e,t}} &= \gamma_{M,t}(-q_{m,t}+w^0_{spec}) \Leftrightarrow f_{\varphi_{e,t}}(1,0)=-q_{m,t}+w^0_{spec}, && (48)
\end{aligned}
$$

Thus, the inflation risk premium decreases with $\gamma_{m,t}$, but increases with both $q_{m,t}$, provided that w^0_{spec} is not too negative. The four second order terms are given by

$$
\begin{aligned}
f_{\gamma_{m,t}\gamma_{m,t}} &= 0, f_{\varphi_{e,t}\varphi_{e,t}}=0, && (49)\\
f_{\gamma_{m,t}\varphi_{e,t}} &= f_{\varphi_{e,t}\gamma_{m,t}}=-q_{m,t}+w^0_{spec} \Leftrightarrow f_{\gamma_{m,t}\varphi_{e,t}}(1,0,-1)=1+w^0_{spec}, && (50)
\end{aligned}
$$

The second line implies that $f_{\varphi_{e,t}}$ increases with $\gamma_{M,t}$.

F Testable implications II

In this appendix we derive additional testable implications when Q_t varies with $q_{m,t}$. In this case, we expand around $\gamma_{m,t}=1$, $\varphi_{e,t}=0$ and $q_{m,t}=-1$. Thus, start from $Q_t=f(\gamma_{m,t},\varphi_{e,t},q_{m,t})=\gamma_{m,t}((1-\varphi_{e,t})q_{m,t}+\varphi_{e,t}w^0_{spec})$ and expand around the base case scenario given by the point $(1,0,-1)$. We present only the with respect to $q_{m,t}$, because the derivatives for $\gamma_{m,t}$ and $\varphi_{e,t}$ are unchanged with $q_{m,t}=-1$.

The first order derivative is given by

$$
f_{q_{m,t}}=\gamma_{M,t}(1-\varphi_{e,t}) \Leftrightarrow f_{q_{m,t}}(1,0,-1)=1,
$$

which means that the inflation risk premium increases with $q_{m,t}$. The relevant second order terms are

$$
\begin{aligned}
f_{q_{m,t}q_{m,t}} &= 0, && (51)\\
f_{\gamma_{m,t}q_{m,t}} &= f_{q_{m,t}\gamma_{m,t}} = (1-\varphi_{e,t}) \Leftrightarrow f_{\gamma_{m,t}q_{m,t}}(1,0,-1) = 1, && (52)\\
f_{\varphi_{e,t}q_{m,t}} &= f_{q_{m,t}\varphi_{e,t}} = -\gamma_{M,t} \Leftrightarrow f_{q_{m,t}\varphi_{e,t}}(1,0,-1) = -1. && (53)
\end{aligned}
$$

The second line implies that $f_{q_{m,t}}$ increases with $\gamma_{M,t}$. The third line implies that $f_{q_{m,t}}$ decreases with $\varphi_{e,t}$.

Table I: Summary statistics for the two-way sort on Inflation Beta and Size

This table presents portfolios at the intersection of two independent sorts in ten inflation beta groups (row: High to Low) and three Size groups (column: Micro, Small and Big). The sample period is August 1964 to December 2011. To conserve space, we present results only for beta groups 1 (High), 4, 7 and 10 (Low) as well as a High minus Low spreading portfolio (HLIB). Columns headed "Size-ctr" present the average across size groups. Inflation betas come from a regression of a stock's past returns on inflation innovations π_t in Panel A and B and total inflation in the real-time vintage CPI series I_t^{rv} in Panel C. In Panel B this regression controls for exposure to the benchmark factors of the CAPM (MKT), FF3M (+SMB, HML) and FFCM (+MOM). Pre-ranking beta is the average inflation beta in a portfolio averaged over time. Post-ranking beta comes from a regression of portfolio returns on the relevant inflation measure (with controls in Panel B). Here, standard errors are Newey-West with 1 lag. Average return and standard deviation are annualized. Panel D presents the characteristics Size, Book-to-Market and Prior Return (averaged within group and over time) and tests these for the HLIB portfolio for the full sample period as well as Pre- and Post-TIPS. ***,**,* denote significance at the 1, 5 and 10 percent level.

Table I continued

Panel A: Inflation Innovation (π_t) Beta and Size

	Micro	Small	Big	Size-ctr	Micro	Small	Big	Size-ctr
	Pre-ranking Beta				Post-ranking Beta			
High	5.28	4.90	4.41	4.86	-0.42	-0.75	-0.55	-0.58
4	-1.54	-1.56	-1.56	-1.55	-1.66	-2.58	-2.68**	-2.31
7	-4.77	-4.77	-4.76	-4.77	-2.28	-2.70	-2.46*	-2.48
Low	-10.93	-10.90	-10.66	-10.83	-3.22	-4.25**	-2.94*	-3.47*
HLIB	16.20	15.81	15.07	15.69	2.80***	3.49***	2.39**	2.89***
	Average Return				Standard Deviation			
High	6.95**	6.11*	2.38	5.15	24.29	25.24	23.62	22.74
4	9.11***	7.73***	4.15*	7.00***	22.47	20.42	16.77	18.54
7	10.02***	9.07***	4.38*	7.82***	22.48	20.70	16.97	19.00
Low	9.71***	10.63***	7.94***	9.43***	25.21	23.97	20.47	22.10
HLIB	-2.76	-4.51*	-5.56**	-4.28**	12.03	16.78	19.40	13.92

Panel B: Sorts control for benchmark factors; Panel C: Inflation I_t^{rv}

	Panel B: Post-ranking Beta			Panel B: Average Return			Panel C: Post-ranking Beta	Panel C: Average Return
Size-ctr	CAPM	FF3M	FFCM	CAPM	FF3M	FFCM	No controls	
High	2.09***	1.92***	1.91***	6.20*	7.14**	7.38**	-0.81	6.55**
4	0.18	0.30*	0.16	8.27***	7.30***	7.88***	-1.76*	8.29***
7	-0.16	0.08	-0.02	7.86***	7.72***	7.58***	-1.91*	7.92***
Low	-0.63	-0.71**	-0.59**	9.71***	9.17***	9.20***	-2.15*	8.26**
HLIB	2.72***	2.63***	2.50***	-3.51*	-2.04	-1.82	1.34***	-1.70

Panel D: Characteristics

	Size			Book-to-Market			Prior return		
Size Ctr	Full	Pre-TIPS	Post-TIPS	Full	Pre-TIPS	Post-TIPS	Full	Pre-TIPS	Post-TIPS
High	1.28	0.66	2.63	0.96	1.05	0.76	17.01	11.97	28.09
4	1.81	0.84	3.92	0.93	1.02	0.72	11.19	9.43	15.07
7	1.92	0.63	4.75	0.88	0.95	0.73	11.20	11.42	10.71
Low	1.51	0.41	3.94	0.83	0.89	0.71	13.11	13.73	11.75
HLIB	-0.23***	0.25***	-1.30***	0.13***	0.16***	0.05	3.90***	-1.75	16.33***

Table II: Forecasting returns of Inflation Beta-sorted portfolios with $TIPS_t$ and $CFNAI_t$

This table presents evidence that returns of Inflation Beta-sorted portfolios vary over time with the market share of TIPS ($TIPS_t$) and over the business cycle ($CFNAI_t$). The sample period is July 1967 to December 2011. We consider three predictive regressions: Model (A) includes only $TIPS_t$; Model (B) adds $CFNAI_t$ and an interaction; and, Model (C) additionally controls for the standard predictors (Dividend Yield, Default Spread, Risk-Free Rate and Term Spread). In Panel A, we present results for five Size-controlled π_t-beta portfolios (High, 4, 7, Low and HLIB). Panel B presents results for sorts that control for the benchmark factors of the CAPM, FF3M and FFCM, whereas Panel C presents results for the truly out-of-sample sort on total inflation in the vintage CPI series I_t^{rv} I_t. Panel D presents long- horizon regressions for k-month compounded returns ($k = 3, 12, 24$). In each panel, the first nine columns present the estimated slope coefficients and adjusted-R^2 (x100). Column ten presents the p-value (in brackets) of a Wald-test of the hypothesis that $TIPS_t$, $CFNAI_t$ and $TIPS_t\times$ $CFNAI_t$ are insignificant in Models (B) and (C). ***,**,* denote significance at the 1, 5 and 10 percent level, respectively, using Newey-West standard errors with k lags.

Table II continued

$$R_{t+1} = \lambda_0 + \lambda_1 TIPS_t + \lambda_2 CFNAI_t + \lambda_3 (TIPS_t \times CFNAI_t) + (controls) + u_{t+1}$$

Panel A: Size-controlled π_t-beta portfolios

	λ_0	λ_1	λ_2	λ_3	c_{DY}	c_{DS}	c_{RF}	c_{TS}	R^2	$H_0: \lambda_1 = \lambda_2 = \lambda_3 = 0$
High (A)	2.10	4.93							0.19	
(B)	3.55	-0.54	-3.60	-5.08					1.08	(0.424)
(C)	6.90	-5.51	-2.54	-2.59	16.35**	2.10	-24.16***	-4.10	2.88	(0.717)
4 (A)	5.51*	2.17							-0.08	
(B)	7.01**	-1.71	-7.62**	-1.96					1.36	(0.061)
(C)	9.31**	-5.14	-6.55**	-0.26	10.79**	1.38	-14.33*	0.99	2.86	(0.148)
7 (A)	6.91*	0.83							-0.17	
(B)	8.39**	-1.88	-9.94***	0.14					1.47	(0.031)
(C)	11.11***	-5.82	-8.26**	2.34	11.39**	3.31	-16.23**	0.46	3.30	(0.053)
Low (A)	8.87**	-0.92							-0.17	
(B)	10.45**	-3.31	-11.77***	1.10					1.39	(0.028)
(C)	13.90***	-8.67*	-10.18**	3.25	9.35	4.48	-17.30*	-0.71	2.36	(0.022)
HLIB (A)	-6.77***	5.85**							1.22	
(B)	-6.90***	2.77	8.17***	-6.18**					4.21	(0.001)
(C)	-7.01***	3.16	7.64***	-5.84**	7.00	-2.38	-6.86	-3.39	4.32	(0.005)

Panel B: Sorts control for benchmark factors

					CAPM: MKT					
HLIB (A)	-6.15***	5.01*							1.02	
(B)	-6.04***	2.62	4.08	-4.06*					2.08	(0.085)
					FF3M: MKT, SMB and HML					
HLIB (A)	-4.80***	5.60**							1.98	
(B)	-4.43**	3.14	1.44	-3.29					2.83	(0.144)
					FFCM: MKT, SMB, HML and MOM					
HLIB (A)	-4.74***	5.96**							2.48	
(B)	-4.35***	3.30	1.60	-3.57					3.68	(0.076)

Panel C: Size-controlled I_t^{rv}-beta portfolios

High (A)	3.18	5.52							0.29	
(B)	4.68	0.10	-4.20	-4.83					1.22	(0.384)
4 (A)	6.90**	2.10							-0.08	
(B)	8.46**	-2.13	-7.53**	-2.39					1.48	(0.066)
7 (A)	6.95*	0.51							-0.18	
(B)	8.33**	-1.85	-9.65***	0.44					1.21	(0.060)
Low (A)	7.95*	-1.19							-0.17	
(B)	9.52**	-2.61	-13.73***	2.85					1.60	(0.027)
HLIB (A)	-4.77*	6.70**							1.46	
(B)	-4.84*	2.71	9.52***	-7.68**					5.46	(0.001)

Panel D: Long-horizon regressions

					$R_{t+1:t+3}$					
HLIB (A)	-6.82***	6.65**							4.27	
(B)	-6.77***	3.48	6.50***	-5.60***					10.28	(0.000)
					$R_{t+1:t+12}$					
HLIB (A)	-6.33***	7.64***							15.92	
(B)	-6.53***	6.67***	4.25**	-2.28**					21.09	(0.000)
					$R_{t+1:t+24}$					
HLIB (A)	-5.90***	8.46***							26.53	
(B)	-5.76***	6.93***	1.75	-1.68*					28.93	(0.000)

Table III: Summary statistics and predictability of asset-pricing factors This table presents the factors we use in our cross-sectional asset pricing tests: INF, MKT, SMB, HML and MOM. The inflation factor INF is constructed similar to SMB, HML and MOM using an independent double sort in three Inflation innovation (π_t) beta groups and two Size groups. Panel A presents annualized average return and standard deviation. Panel B presents the usual forecasting exercise of returns on $TIPS_t$ in Model (A) and in addition on $CFNAI_t$ and their interaction in Model (B). For each factor, we also present the p-value (in brackets) of a Wald test of the hypothesis that the factor risk premium is not time-varying in Model (B). ***,**,* indicate significance at the 1, 5 and 10 percent level, respectively, using Newey-West standard errors with 1 lag.

Panel A: Summary statistics

	INF	MKT	SMB	HML	MOM
Avg. Ret.	-1.60	5.07**	2.49	4.60***	8.37***
St.Dev.	9.90	16.13	11.05	10.41	15.33

Panel B: $F_{t+1} = \lambda_0 + \lambda_1 TIPS_t + (\lambda_2 CFNAI_t + \lambda_3(TIPS_t \times CFNAI_t) + u_{t+1}$

	INF		MKT		SMB		HML		MOM	
	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)
λ_0	-3.35**	-3.61**	4.95*	5.75**	1.86	2.60	5.71***	5.55***	11.78***	10.20***
λ_1	3.31**	1.91	0.23	-1.33	1.17	-0.07	-2.10	-2.60*	-6.42	1.62
λ_2		5.85***		-5.20*		-5.17***		2.88		-0.75
λ_3		-3.51***		-0.09		0.27		-1.52		9.46**
R^2	0.74	3.23	-0.19	0.25	-0.09	1.12	0.15	0.35	1.28	6.77
$H_0 : \alpha_1 =$ $\alpha_2 = \alpha_3 = 0$		(0.000)		(0.248)		(0.008)		(0.110)		(0.151)

Table IV: The time-varying inflation risk premium in cross-sectional regressions

This table presents cross-sectional regressions for portfolios (in Panel A to D) and individual stocks (Panel E), where we allow for time-varying risk premiums. In case of portfolios, the first-stage betas used as independent variables in the second stage are the usual constant, full sample betas. In case of individual stocks, we use the time-varying betas that use only historical data and were used to sort. Column-wise we consider the benchmark factor models (CAPM, FF3M and FFCM) as well as models that add inflation risk. We consider three specifications of the risk premiums. Type (A) is the standard Fama-MacBeth cross-sectional regression estimate of the unconditional risk premium (standard errors are Shanken-corrected in Panels A to D and Fama-MacBeth in Panel E). Type (B) and (C), respectively, allow the risk premiums to vary over time with $TIPS_t$ and $TIPS_t$, $CFNAI_t$ and $TIPS_t \times CFNAI_t$. In Panels A to D these conditional risk premiums are estimated using the pooled time-series cross-sectional regression described in Section VI (with standard errors clustered on time). In Panel E the conditional risk premiums are estimated using a three stage regression procedure, where we regress the second stage Fama-MacBeth estimates on the instruments (standard errors are Newey-West with 1 lag). In Panel A, we use 30 Inflation Beta and Size-sorted portfolios as test assets. Panel B adds 17 industry portfolios and 25 Size and Book-to-Market portfolios to the set of test assets. Panel C replaces the traded inflation factor INF with the non-traded inflation innovation π_t. In Panel D and E we additionally control for the characteristics Size, Book-to-Market and Momentum (Prior return). In Panel A we present the full set of results: the estimated risk premiums (λ's, where $(\lambda_0, \lambda_1, \lambda_2, \lambda_3)$ refer to the instrument vector $(1, TIPS_t, CFNAI_t, TIPS_t \times CFNAI_t)$), the time-series average of the second stage cross-sectional regression R^2, a Wald test of the hypothesis that the inflation risk premium does not vary over time and the model-implied inflation risk premium at the beginning and the end of the sample period. For the sake of comparison, the implied risk premium in Panel C (Panel E) is scaled by the post-ranking (pre-ranking) inflation beta of the HLIB portfolio analyzed in Table 1. To conserve space, Panels B to E present everything but the estimated risk premiums, which are reported in Table B2 of Appendix B. The cross-sectional regressions never include an intercept. ***,**,* indicate significance at the 1, 5 and 10 percent level, respectively.

Table IV continued

Panel A: 30 Inflation beta and Size portfolios

		CAPM	CAPM+INF			FF3M	FF3M+INF			FFCM	FFCM+INF		
		(A)	(A)	(B)	(C)	(A)	(A)	(B)	(C)	(A)	(A)	(B)	(C)
MKT	λ_0	6.43**	6.31**	5.48*	6.79**	5.47**	5.38**	5.01*	5.84**	5.72**	5.61**	5.44*	6.14**
	λ_1			1.57	-1.61			0.70	-0.96			0.32	-0.97
	λ_2				-7.12**				-5.28**				-4.70*
	λ_3				-1.32				-0.18				0.06
SMB	λ_0					0.33	1.64	2.00	2.49	1.07	1.49	1.70	2.28
	λ_1							-0.66	-1.55			-0.41	-1.55
	λ_2								-3.34				-3.74*
	λ_3								0.07				-0.09
HML	λ_0					6.82	3.16	-0.15	1.50	6.67	4.97	3.25	3.89
	λ_1							6.24**	0.13			3.25	0.05
	λ_2								-4.34				0.20
	λ_3								-5.57**				-3.72
MOM	λ_0									3.27	2.06	6.99	4.06
	λ_1											-9.31	-0.25
	λ_2												11.68**
	λ_3												6.57
INF	λ_0		-2.52	-4.22**	-4.69***		-2.06	-4.04**	-4.29***		-2.07	-4.06**	-4.30***
	λ_1			3.21**	2.20			3.74**	1.98			3.76**	1.98
	λ_2				7.32***				6.53***				6.51***
	λ_3				-3.55***				-4.15***				-4.16***
Average	R_t^2 from 2nd stage	4.41	20.95	20.95	20.95	35.63	44.43	44.43	44.43	40.09	46.92	46.92	46.92
INF	$H_0 : \lambda_1 = \lambda_2 = \lambda_3 = 0$				(0.000)				(0.000)				(0.000)
INF	July 1967			-4.22**	-8.58***			-4.04**	-7.76***			-4.06**	-7.76***
INF	December 2011			8.68	5.44			10.99*	5.55			11.03*	5.55

Panel B: Extended set of 72 portfolios

		CAPM	CAPM+INF			FF3M	FF3M+INF			FFCM	FFCM+INF		
		(A)	(A)	(B)	(C)	(A)	(A)	(B)	(C)	(A)	(A)	(B)	(C)
Average	R_t^2 from 2nd stage	5.44	13.69	13.69	13.69	27.77	36.98	36.98	36.98	29.61	39.33	39.33	39.33
INF	$H_0 : \lambda_1 = \lambda_2 = \lambda_3 = 0$				(0.000)				(0.000)				(0.000)
INF	July 1967			-4.70***	-8.75***			-3.77**	-7.81***			-4.38***	-8.23***
INF	December 2011			6.92	4.69			8.01	4.64			8.80	4.00

Table IV continued

Panel C: Cross-sectional regressions using non-traded inflation risk π_t

	30 Portfolios									72 Portfolios		
	CAPM+π_t			FF3M+π_t			FFCM+π_t			FFCM+π_t		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Average R_t^2 from 2nd stage	15.76	15.76	15.76	41.10	41.10	41.10	43.34	43.34	43.34	38.47	38.47	38.47
π_t $H_0 : \lambda_1 = \lambda_2 = \lambda_3 = 0$			(0.001)			(0.001)			(0.009)			(0.005)
π_t July 1967		-4.56***	-7.43***		-4.58***	-6.51***		-3.28**	-5.06***		-2.27*	-4.73***
π_t December 2011		12.20	3.00		11.64	1.03		5.18	-2.11		5.27	1.91

Panel D: Cross-sectional regressions including characteristics

	30 Portfolios									72 Portfolios		
	CAPM+π_t			FF3M+π_t			FFCM+π_t			FFCM+π_t		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Average R_t^2 from 2nd stage	46.77	46.77	46.77	51.73	51.73	51.73	52.96	52.96	52.96	44.00	44.00	44.00
π_t $H_0 : \lambda_1 = \lambda_2 = \lambda_3 = 0$			(0.000)			(0.000)			(0.001)			(0.001)
π_t July 1967		-5.55***	-9.92***		-5.62***	-10.07***		-5.76***	-10.18***		-5.43***	-8.97***
π_t December 2011		11.77**	4.72		13.53**	5.51		13.52**	5.58		9.73	2.26

Panel E: Three-stage regressions using individual stocks

	FF3M+π_t						FFCM+π_t					
	Without			With			Without			With		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Average R_t^2 from 2nd stage	3.12	3.12	3.12	4.73	4.73	4.73	3.29	3.29	3.29	4.87	4.87	4.87
π_t $H_0 : \lambda_1 = \lambda_2 = \lambda_3 = 0$			(0.074)			(0.100)			(0.069)			(0.095)
π_t July 1967		-2.55*	-2.50		-4.80***	-5.26***		-2.42*	-2.51		-4.56***	-4.95***
π_t December 2011		19.97**	9.72		11.98	10.61*		19.75**	9.70		11.66	10.63*

Table V: Pricing of exposure to TIPS in the stock market relative to realized TIPS returns

This table presents a test of the hypothesis that the risk premium in the stock market for a unit exposure to TIPS converges to the realized returns of TIPS towards the end of the sample, as predicted by our model. Panel A presents Fama and MacBeth (1973) cross-sectional regressions using the 30 Inflation Beta and Size-sorted portfolios (UI1S30) as test assets. The factors are the CRSP VW market portfolio and a portfolio of TIPS. The exposures are estimated over 60 month rolling windows, to alleviate concerns about noisy TIPS prices in the market's early years. Over the full sample ('97-'11) and for each of three five-year subperiods, we report: average estimated risk premiums (e.g., $\lambda_{TIPS} = \frac{1}{T}\sum_{t=1}^{T}\lambda_{TIPS,t+1}$), Fama and MacBeth (1973) t-statistics (in parenthesis) and average cross-sectional R^2's. The fourth and fifth column, respectively, report average realized TIPS returns ($r_{TIPS} = \frac{1}{T}\sum_{t=1}^{T} r_{TIPS,t+1}$) and a test of the difference between TIPS returns and the estimated TIPS risk premium in the cross-sectional regression ($r_{TIPS} - \lambda_{TIPS}$). Panel B presents the same cross-sectional regressions, but with the inflation factor INF substituted for the portfolio of TIPS. The final column presents the time-series average of the cross-sectional correlation between the risk premiums predicted by the two models for the 30 portfolios: $corr(\widehat{r^{(1)}_{t,t+1}}, \widehat{r^{(2)}_{t,t+1}})$.

	Panel A: TIPS risk premium and TIPS returns					Panel B: Benchmark INF risk premium			
	(1) $r_{i,t+1} = \lambda_{MKT,t+1}\widehat{\beta_{MKT,t}} + \lambda_{TIPS,t+1}\widehat{\beta_{TIPS,t}} + u_{i,t+1}$			Realized	Difference	(2) $r_{i,t+1} = \lambda_{MKT,t+1}\widehat{\beta_{MKT,t}} + \lambda_{INF,t+1}\widehat{\beta_{INF,t}} + u_{i,t+1}$			
	λ_{MKT}	λ_{TIPS}	R^2	r_{TIPS}	$\lambda_{TIPS} - r_{TIPS}$	λ_{MKT}	λ_{INF}	R^2	$corr(\widehat{r^{(1)}_{i,t+1}}, \widehat{r^{(2)}_{i,t+1}})$
'97-'11	4.90	7.34	0.09	4.30	3.04	7.59	0.85	0.12	0.40
	(1.03)	(2.03)		(2.79)	(0.77)	(1.57)	(0.25)		
'97-'01	3.57	10.17	0.20	1.45	8.72	9.89	-8.75	0.11	-0.03
	(0.39)	(2.66)		(1.07)	(2.15)	(1.10)	(-1.06)		
'02-'06	7.57	5.26	-0.09	4.85	0.41	10.75	2.11	-0.06	0.60
	(1.32)	(0.88)		(1.68)	(0.06)	(1.59)	(0.67)		
'07-'11	3.54	6.56	0.18	6.66	-0.11	1.95	9.48	0.30	0.65
	(0.38)	(0.78)		(1.97)	(-0.01)	(0.21)	(1.89)		

Table VI: Do the inflation factor and TIPS really hedge inflation risk? This table presents hedge regressions of $ARMA(1,1)$-innovations in inflation (π_t, Panel A) and total inflation (I_t, Panel B) on gross returns of (1) the one-month t-bill ($R_{TB1,t}$), (2) the 10 year constant maturity treasury bond ($R_{CMT10,t}$), (3) the inflation factor ($R_{INF,t}$) and (4) a portfolio of TIPS ($R_{TIPS,t}$). Multiple regressions (5) and (6) combine these assets in the optimal hedge portfolio. We present the regressions for two sub-periods: Pre-TIPS (1964-08 to 1997-02) and Post-TIPS (1997-03 to 2011-12). ***,**,* denote significance at the 1, 5 and 10 percent level, respectively, using Newey-West standard errors with 1 lag.

E.g., $\pi_t = a + b_{TB1} R_{TB1,t} + b_{CMT10} R_{CMT10,t} + b_{INF} R_{INF,t} + b_{TIPS} R_{TIPS,t} + e_t$

Model (#)	a	b_{TB1}	b_{CMT10}	b_{INF}	b_{TIPS}	R^2
Panel A: $ARMA(1,1)$-innovations in inflation (π_t)						
			Pre-TIPS			
(1)	-0.001**	0.156***				2.17
(2)	0.000***		-0.011**			1.18
(3)	0.000***			0.020***		4.07
(5)	-0.001**	0.175***	-0.010*	0.019***		7.34
			Post-TIPS			
(1)	0.000	0.025				-0.55
(2)	0.000		-0.028*			3.22
(3)	0.000			0.011*		1.06
(4)	0.000				0.017	0.32
(6)	0.000	0.081	-0.066**	0.004	0.073**	11.32
Panel B: Total Inflation (I_t)						
			Pre-TIPS			
(1)	0.001	0.694***				23.94
(5)	0.001	0.722***	-0.017**	0.015**		26.91
			Post-TIPS			
(1)	0.002***	0.157				0.20
(6)	0.001***	0.203	-0.068**	-0.001	0.072**	11.12

Table VII: The inflation risk premium and the nominal-real covariance
This table presents evidence linking the stock market-based inflation risk premium to the nominal-real covariance, as is done in Campbell et al. (2013) for nominal bonds. In Panel A, we present our proxies of the nominal-real covariance. We regress (cumulative) log future Industrial Production growth and Non-Durables and Services Consumption growth on lagged inflation, and calculate the negative of the stock market beta of the ten year constant maturity bond. We present the coefficients and R^2's for various sub-periods, starting from February 1959 (coinciding with the availiability of monthly consumption data) to December 2011. In Panel B, we forecast the inflation risk premium (measured by the return on the inflation factor INF) one month-ahead (or compounded twelve month-ahead) with running estimates of the nominal-real covariance. These running estimates use only historical data as described in Section VI.A. We present results for three models. Model (A) includes only the estimated running proxy of the nominal-real covariance ($\widehat{b_{IP,t}}$, $\widehat{b_{CG,t}}$ or $\widehat{b_{B,t}}$, which are standardized); Model (B) adds $CFNAI_t$ and an interaction term; and, Model (C) adds $TIPS_t$ and $TIPS_t \times CFNAI_t$. We present the estimated coefficients, adjusted R^2's and a Wald test of the hypothesis that the terms related to the nominal-real covariance are jointly insignificant in a model that includes $TIPS_t$, $CFNAI_t$ and $TIPS_t \times CFNAI_t$. In Panel C, we present select results for the Pre- and Post-TIPS period. ***,**,* indicate significance at the 1, 5 and 10 percent level, respectively, using Newey-West standard errors with k lags.

Table VII continued

Panel A: Time-varying nominal-real covariance

		$S_{t:t+k} = a + b_S I_{t-1} + e_{t:t+k}$				$R_{B10,t+1} = a + b_B(-R_{M,t+1}) + e_{t+1}$	
		S = Industrial production		S = Consumption		-Long-Term Bond Beta	
	k	b_{IP}	R^2	b_{CG}	R^2	bB	R^2
Full sample	1	-0.32	1.33	-0.09*	0.58	-0.07**	1.67
	12	-4.74***	9.61	-0.76	2.67		
1967-07 to	1	-0.80**	6.81	-0.35***	6.86	-0.16***	13.05
1979-12	12	-10.58***	26.60	-1.88***	14.29		
1980-01 to	1	-0.64**	7.47	-0.20*	2.52	-0.17*	6.13
1989-12	12	-5.37***	18.44	-1.90***	30.03		
1990-01 to	1	-1.15***	11.81	-0.27	2.05	-0.15**	9.70
1999-12	12	-7.68***	22.62	-3.69***	32.66		
2000-01 to	1	0.34	1.59	0.04	-0.41	0.13***	7.95
2011-12	12	-1.86	0.81	0.04	-0.75		

Panel B: Predicting the inflation risk premium using proxies for the nominal-real covariance

$$R_{INF,t:t+k} = \lambda_0 + \lambda_1 TIPS_t + \lambda_2 CFNAI_t + \lambda_3 (TIPS_t \times CFNAI_t) + \\ \lambda_4 \widehat{b_{S,t}} + \lambda_5 (\widehat{b_{S,t}} \times CFNAI_t) + \lambda_6 (\widehat{b_{S,t}} \times TIPS_t) + u_{t:t+k}$$

	k		λ_0	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	R^2	$H_0: \lambda_4 = \lambda_5 = \lambda_6 = 0$
					S = Industrial Production ($\widehat{b_{IP,t}}$)						
INF	1	(A)	-1.60				3.73***			1.00	
		(B)	-1.89		2.01		2.97**	-3.06**		2.65	
		(C)	-2.65	-0.29	5.97**	-3.90**	2.38	0.41	0.20	2.92	(0.558)
	12	(A)	-1.40				3.17***			8.63	
		(B)	-1.89		1.68		3.56***	-2.32**		17.77	
		(C)	-2.73**	-3.69	4.73***	-2.11***	1.09	1.52	4.48*	27.75	(0.144)
					S = Consumption Growth ($\widehat{b_{CG,t}}$)						
INF	1	(A)	-1.60				2.45			0.32	
		(B)	-1.68		1.05		1.65	-3.26**		1.74	
		(C)	-3.28*	-2.41	6.46**	-4.15**	0.59	0.74	3.03	2.85	(0.835)
	12	(A)	-1.40				4.04***			14.15	
		(B)	-1.33		0.79		3.66***	-1.57		17.95	
		(C)	-2.77***	-2.29	3.79***	-1.91***	1.76*	0.79	3.63	28.69	(0.142)
					S = Bond beta ($\widehat{b_{B,t}}$)						
INF	1	(A)	-1.60				2.26*			0.25	
		(B)	-2.83*		3.51**		2.51**	-6.15***		3.18	
		(C)	-2.89	-1.88	4.96***	-2.26	1.69	-2.97	1.34	2.89	(0.839)
	12	(A)	-1.40				2.91***			7.24	
		(B)	-2.13*		2.55***		3.11***	-3.56***		20.07	
		(C)	-2.66**	-12.00	3.26**	-0.65	0.13	-1.01	9.18*	30.99	(0.223)

Panel C: Pre- versus Post-TIPS era (S = Industrial Production ($\widehat{b_{IP,t}}$))

						Pre-TIPS					
INF	1	(A)	-2.20				2.19			0.34	
		(B)	-2.18		5.17**		1.43	-0.12		3.27	
		(C)									
						Post-TIPS					
INF	1	(A)	-0.38				6.29*			1.45	
		(B)	-1.86		0.40		5.55	-4.38		1.69	
		(C)	-6.19	5.29	14.10	-5.37	13.30	-3.60	-6.20	2.81	(0.410)

III State variables, macroeconomic activity and the cross-section of individual stocks

Abstract

I revisit the question of whether risk premiums for ICAPM-motivated state variables are consistent with how these variables predict consumption-investment opportunities. To this end, I run long-horizon regressions for macroeconomic activity and cross-sectional regressions for individual stocks. I find that the state variable risk premiums in the cross-section are consistent with investor's incentives to hedge against the systematic economic news that the state variables contain in the time-series. This finding adds to existing portfolio-level evidence that is mixed on the issue of pricing, but, as shown in Maio and Santa-Clara (2012), certainly suggestive that risk premiums are not consistent with the ICAPM of Merton (1973).

I link the time-series to the cross-section in the context of asset pricing. I find that risk premiums in the cross-section of individual stocks for exposure to Intertemporal CAPM (ICAPM) motivated state variables are consistent with how these variables predict macroeconomic activity in the time-series. This time-series and cross-sectional consistency alleviates concerns about "factor fishing" and is consistent with the idea that investors desire to hedge against shocks to macroeconomic activity. This finding resuscitates a central role for business cycle risk in asset pricing along the lines suggested by Cochrane (2005, Ch. 9) and Koijen et al. (2013).

The empirical method consists of two elements. First, long-horizons regressions establish whether and how a candidate state variable forecasts macroeconomic activity, as measured by Industrial Production growth or the Chicago FED National Activity Index. Second, to establish whether this state variable is a priced risk factor, I directly identify the individual stocks that are exposed to innovations in the state variable. Following Campbell (1996), these innovations are taken from a $VAR(1)$.[1] I use these exposures to run cross-sectional regressions and sort stocks into portfolios. In this way, I use a broad and heterogenous cross-section of exposures, which is attractive for hedging. Moreover, using individual stocks responds to recent asset pricing literature that suggests firm-level tests are relatively efficient (Litzenberger and Ramaswamy (1979) and Ang et al. (2011)), whereas inferences from portfolio-level tests depend critically on the chosen set of

[1]Note, measuring exposures to innovations in the state variables, rather than their levels, separates this work from versions of the Conditional CAPM in Jagannathan and Wang (1996) and Cochrane (1996).

test portfolios (Ahn et al. (2009) and Lewellen et al. (2010)).

The main contribution of this study is in establishing that these two elements are consistent in sign. The sign restriction follows from a stochastic discount factor that prices systematic economic news and therefore exposure to state variables that contain this news. This sign restriction is a simple alternative to directly imposing intertemporal restrictions on the risk prices, such as in the $VAR-ICAPM$ of Campbell (1996), to guard against "factor fishing". This concern traditionally undermines tests of the ICAPM (Fama (1991) and Black (1993)). Indeed, existing portfolio-level evidence on the pricing of these state variables is mixed, but certainly suggestive that pricing is inconsistent with how the state variables predict the aggregate stock market portfolio, which relation is implied by the ICAPM of Merton (1973) (see Maio and Santa-Clara (2012)).[2] However, the aggregate stock market return is likely a poor proxy for the return on aggregate wealth (Roll (1977)), which is the opportunity set of interest to the representative investor. Because investors own human capital, houses, shares of small businesses and other non-marketed assets, besides stocks and bonds, Cochrane (2005, Ch. 9) advocates the search for "recession state variables", i.e., variables that predict macroeconomic activity.

To start out, I focus on the three most commonly used state variables in the literature: Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). I find that DS forecasts negative changes in macroeconomic activity (consistent with Chen (1991) and Gilchrist and Za-

[2] A long history of papers test whether ICAPM-motivated state variables are priced in a set of predetermined portfolios. An incomplete list includes Shanken (1990), Ferson and Harvey (1991), Campbell (1996), Brennan et al. (2004), Petkova (2006), Hahn and Lee (2006) and Kan et al. (2012).

krajsek (2012)), TS forecasts positive changes (consistent with Estrella and Hardouvelis (1991) and Adrian and Estrella (2008)), whereas DY is not a robust predictor. Thus, the ICAPM suggests that only exposures to DS and TS risk are priced. Moreover, the ICAPM suggests that the DS risk premium is negative and the TS risk premium positive. Indeed, high DS and low TS exposure stocks pay off when macroeconomic activity is expected to decrease, which makes these stocks attractive as a hedge and lowers their expected returns. Consistent with these predictions, I estimate an annualized average risk premium of -6.5% for DS, 6.0% for TS and around zero for DY in quarterly cross-sectional regressions. The corresponding absolute Sharpe ratio is large at 0.41 and 0.48 for DS and TS, respectively, relative to 0.30 for the market portfolio.

Next, I show that this time-series and cross-sectional consistency is general to the broader set of ICAPM-motivated state variables analyzed in Maio and Santa-Clara (2012). First, I analyze the model of Petkova (2006), which includes the risk-free rate (RF) next to DY, DS and TS.[3] Second, the model of Campbell and Vuolteenaho (2004), which includes TS, the price-earnings ratio (PE) and the value spread (VS). Third, the model of Koijen et al. (2013), which includes the Cochrane and Piazzesi (2005) bond market factor (CP) and a factor that measures the level of the term-structure (LVL). In the long-horizon regressions, RF and VS forecast negative changes in macroeconomic activity, CP forecasts positive changes, whereas PE and LVL

[3] Inspired by Lioui and Poncet (2011), who highlight multicolinearity problems between RF and TS, I consider two versions. First, I substitute RF for TS. Second, I add RF orthogonalized from TS to the original set of state variables. The latter version shows that RF has little to add to a model that already includes TS in both the time-series and the cross-section.

are not robust predictors. Consistent with this time-series evidence, I estimate that RF, VS and CP capture an annualized risk premium of -4.0%, -5.5% and +4.5% (an absolute Sharpe ratio of 0.26, 0.38 and 0.33), respectively, whereas PE and LVL risk are not priced.

I find that these conclusions are robust. First, the results are consistent when the time-series and cross-sectional regressions are run at the monthly frequency instead. This finding alleviates concerns about potential horizon-effects in the predictive relations and is important because the investment horizon of the representative agent is unknown (Kothari et al. (1995), Campbell (1996) and Brennan and Zhang (2012)). Also, the results are qualitatively similar when using exposures to first-differences in the state variables instead of $VAR(1)$-innovations.

Finally, the risk premiums are consistent in sign and often in magnitude for value- and equal-weighted High minus Low quintile portfolios. This finding suggests suggests that transaction costs are unlikely to eradicate the risk premiums for the priced state variables (DS, TS, RF, VS and CP) completely. These individual stock-based strategies can be thought of as simple, out-of-sample proxies for the maximum correlation portfolio of Breeden et al. (1989). Because I construct portfolios that are maximally exposed ex ante, an important question is whether the portfolios are exposed ex post. I find that they are, which suggests that the state variables are not useless factors in the sense of Kan and Zhang (1999). Combining, the evidence suggests that these strategies are useful for investors that desire to tilt their equity portfolio towards or away from these intertemporal risks.

I conclude that pricing is consistent with investor's incentives to hedge business cycle risk, which extends Koijen et al. (2013), who focus on the pricing of CP alone. This finding advances an ICAPM literature, starting with Chen et al. (1986) and Ferson and Harvey (1991), that routinely includes term structure variables as risk factors. In a closely related paper, Maio and Santa-Clara (2012) conclude however that portfolio-level risk premiums for these state variables are inconsistent with hedging incentives in the ICAPM of Merton (1973). Although, Maio and Santa-Clara (2012) estimate risk premiums for DS, RF, VS and CP that are consistent in sign with my estimates, they are largely insignificant. This finding suggests that using individual stocks is indeed more efficient. It is only in case of VS and CP, however, that the sign of the risk premium is consistent with how the level forecasts aggregate stock market returns. Moreover, while TS predicts positive stock market returns as it does macroeconomic activity, the sign of its risk premium is sensitive to the choice of portfolios. Finally, DY, PE and LVL are not priced among portfolios either, but do forecast stock market returns, especially at longer horizons.[4]

This paper also contributes to the debate on whether the Fama and French (1993) factors proxy for intertemporal risk and, as such, to the risk factor versus characteristics controversy discussed in Fama and French (1992), Daniel and Titman (1997) and Chordia et al. (2012). For instance, results in Petkova (2006) and Hahn and Lee (2006) suggest that SMB and HML can substitute for state variables in portfolio-level tests. I confirm evidence to the contrary in Cederburg (2011) and

[4] Maio and Santa-Clara (2012) find that risk premiums are similarly inconsistent with how the state variables predict market variance and a measure of market Sharpe ratio.

Maio and Santa-Clara (2012). The risk premiums for the priced state variables (DS, TS, RF, VS and CP) are not driven out by exposures to SMB and HML in firm-level cross-sectional regressions.

In contrast, the DS risk premium is captured by the characteristic Size. This Size effect is consistent with Perez-Quiros and Timmermann (2000) and Baker and Wurgler (2012), who argue that small stocks are more sensitive to business cycle variation in credit conditions. Similarly, the CP risk premium is eradicated by including Size and Book-to-Market. The link between CP exposures and Book-to-Market is studied in more detail in Koijen et al. (2013). These findings are perhaps unsurprising, because characteristics can be measured without error, whereas exposures need to be estimated. Yet, TS, RF and VS are not fully driven out by characteristics, which means that these state variables do contain independent information about the cross-section of expected individual stock returns.

The rest of this paper is organized as follows. Section A motivates the link between macroeconomic activity and state variable risk premiums in a stochastic discount factor framework. Section B describes the data and methods used. Section C tests for time-series and cross-sectional consistency in the pricing of state variable risk. Section D analyzes individual stock-based state variable mimicking portfolios. Section E confronts the state variable risk premiums with the Fama and French (1993) factors and characteristics. Section F summarizes and concludes.

A Motivation

Consider the conditional asset pricing model $E_t(m_{t+1}r_{i,t+1}) = 0$, where $r_{i,t+1}$ is the excess return on asset i and m_{t+1} is the stochastic discount factor (SDF) that exists when the law of one price holds, with the expectation taken given investor's information set at time t. In most equilibrium models, the SDF is a nonlinear function of factors and the model's parameters. Following the standard procedure, I assume that the SDF can be approximated by a constant linear function of factors

$$m_{t+1} = a - b'f_{t+1}, \tag{1}$$

where the factors are the return on the market portfolio as in the CAPM and innovations in a set of K state variables ($\varepsilon_{z,k,t+1} = z_{k,t+1} - E_t(z_{k,t+1})$ for $k = 1,..,K$).[5] Thus, $f_{t+1} = (r_{m,t+1}, \varepsilon'_{z,t+1})'$ and $b = (b_m, b'_z)'$.

In this paper, I test the hypothesis that $b_{z,k} > 0$ when $z_{k,t}$ predicts macroeconomic activity with a positive sign and vice versa. This hypothesis can be motivated by a rational ICAPM, where investors wish to hedge their risk exposure to state variables that contain news about future macroeconomic activity, with good news lowering marginal utility (see Chen et al. (1986), Vassalou (2003), Cochrane (2005, Ch. 9) and Koijen et al. (2013) for similar arguments).

This model is similar to the ICAPM of Merton (1973), where exposure to state variables that predict consumption-investment opportunities are priced in addition to market beta. In his economy, there exist

[5]It is straightforward to extend the analysis to allow the SDF-coefficients to vary over time, for instance, as a linear function of instruments (see Cochrane (2005, Ch, 8).

only stocks (and a risk-free asset), such that the opportunity set can be summarized by the first two moments of the aggregate stock market return. The testable implication is that $b_{z,k} > 0$ when $z_{k,t}$ predicts high returns or low volatility or both, in which case marginal utility is low. Using the CRSP value-weighted stock market portfolio, Maio and Santa-Clara (2012) find that for a range of ICAPM-motivated state variables, the estimated risk premiums are generally inconsistent with this logic.

A possible explanation for this inconsistency, which I explore in this paper, follows from Roll's critique (1977) of the CAPM. The aggregate stock return may be poor proxy for the return on the aggregate wealth portfolio, which is the opportunity set of interest to the representative investor. In fact, previous research establishes that state variables, such as the Default Spread (DS) and the Term Spread (TS), predict returns on various components of wealth, which need not all be traded assets (see Cochrane (2005, Ch. 9)). First, both DS and TS predict returns in stock as well as government and corporate bond markets, consistent with their common use as proxies for credit market conditions and the stance of monetary policy, respectively (Keim and Stambaugh (1986) and Fama and French (1989)). In addition, Fama and French (1989) argue that TS captures a term premium that is common to all long maturity assets. Consistent with this argument, Campbell (1996) finds that TS predicts human capital returns. Finally, Hong and Yogo (2012) find that a combination of DS and TS predicts returns in commodity markets, whereas Ang et al. (2013) show that a factor that is common to public and private real estate loads on DS.

A possible solution is to broaden the proxy of the wealth portfolio and include, for instance, non-traded human capital as in Campbell (1996). To sidestep the need to define the exact composition of the wealth portfolio, I follow the advice in Cochrane (Ch. 9) and instead seek "recession state variables", that is, variables forecasting macroeconomic activity.[6] This approach essentially uses macroeconomic growth as a broad proxy for returns on the various components of wealth, such that changes in consumption-investment opportunities are described by those state variables that contain news about future growth rates. Fundamentally, this approach assumes that returns on large components of the wealth portfolio are procyclical, which is consistent with extant evidence of a positive correlation between stocks and, for instance, commodities (Hong and Yogo (2012)), human capital (Campbell (1996)) and real estate (Ang et al. (2013)). Moreover, this procyclicality is present in equilibrium asset pricing theory, as noted in Chen (1991) for stocks and bonds. Since financial securities are claims against output, an increase in the productivity of capital positively impacts expected stock returns (see, e.g., Cox et al. (1985)). At the same time, individuals would want to smooth consumption by attempting to borrow against expected future outputs, thereby bidding up long-term interest rates.

Equation (1) implies the following beta asset pricing model:

$$E_t\left(r_{i,t+1}\right) = \lambda_{m,t}\beta_{i,m,t} + \lambda'_{z,t}\delta_{i,z,t}, \tag{2}$$

[6] By directly defining the proxy, Campbell (1996) is able to derive intertemporal restrictions on the risk prices. Such restrictions are lost in the general SDF-approach applied here.

where $E_t(r_{i,t+1})$ is the expected excess return $(r_{i,t+1} = R_{i,t+1} - R_{f,t+1})$ of asset i; the exposures $\beta_{i,m,t}$ and $\delta_{i,z,t}$ are the slope coefficients from the return-generating process $r_{i,t+1} = \alpha_{i,t} + \beta_{i,m,t} r_{m,t+1} + \delta'_{i,z,t}\varepsilon_{z,t+1} + \nu_{i,t+1}$; and, $\lambda_{m,t}$ and $\lambda_{z,t}$ are the market and state variable risk premiums, respectively, all conditional on the information set at time t. The risk premiums are related to the SDF-specification by $\binom{\lambda_{m,t}}{\lambda_{z,t}} = Var_t(f_{t+1})/E_t(m_{t+1})b$, where $E_t(m_{t+1})$ is positive in the absence of arbitrage opportunities. Thus, an additional component in expected return is required and obtained whenever an asset is influenced by systematic economic news, which is consistent with the general conclusion of asset pricing theory (Chen et al. (1986)).

In the following, I analyze the pricing implications from this model using a standard approach, which entails running Fama and MacBeth (1973) cross-sectional regressions of asset returns on historical betas in each period $t+1$ (for more detail, see Section B). To derive testable unconditional implications, note that the periodic risk premium estimates from these regressions equal the return on a zero-investment portfolio that has a beta of one with respect to each respective factor and a beta of zero with respect to the other factors (Fama (1976)). Let us define these risk premiums as $r^{FMB}_{m,t+1}$ and $r^{FMB}_{z,k,t+1}$ for $k = 1, .., K$ in the context of Equation (2). Moreover, going back to Equation (1), define the factors without loss of generality so as to have conditional mean equal to zero $(f^*_{t+1} = f_{t+1} - E_t(f_{t+1}))$ and normalize the SDF as $m_{t+1} = 1 - b'f^*_{t+1}$, such that $E_t(m_{t+1}) = 1$.

Combining, we have

$$E_t(r^{FMB}_{m,t+1}) = 1 \times \lambda_{m,t} \text{ and } E_t(r^{FMB}_{z,k,t+1}) = 1 \times \lambda_{z,k,t} \text{ for } k = 1, .., K, \quad (3)$$

which conditions down to

$$E(r^{FMB}_{m,t+1}) = \lambda_m \text{ and } E(r^{FMB}_{z,k,t+1}) = \lambda_{z,k} \text{ for } k = 1, .., K, \quad (4)$$

where $\binom{\lambda_m}{\lambda_z} = E(f^*_{t+1} f^{*\prime}_{t+1})b$ by the law of iterated expectations. Thus, in this paper I estimate the unconditionally expected excess return investors require to invest in a portfolio with a conditional factor beta equal to one.

As pointed out in Fama (1996), the sign of the market risk premium in this ICAPM is indeterminate, because it may hedge against state variable risk. However, when the innovations in the state variables are (close to) orthogonal to the market, which is the relevant case in this paper, λ_m is positive and must equal the expected return on the market portfolio. When the innovations are also (close to) orthogonal to each other, the state variable risk premiums in λ_z are multiples of the respective elements of b_z, such that their signs must be identical. Hence, if a state variable predicts economic activity with a positive sign, an asset that covaries with innovations in this state variable earns a positive risk premium. The intuition is that the asset does not allow the investor to hedge against business cycle risk, such that he will not be willing to pay a high price for this asset.

B Methodology and data

This section describes the data and methods used to test the ICAPM derived above. First, I introduce the long-horizon regressions that determine whether a candidate state variable forecasts macroeconomic activity. Second, I introduce the cross-sectional regression that tests whether exposure to the state variable is priced in a consistent manner.

A Predicting macroeconomic activity

I use two measures of macroeconomic activity: the Industrial Production Index (IP) and the Chicago FED National Activity Index (CF). Both indexes are designed to gauge real output and overall economic activity in the US and are available from the FRED® database of the Federal Reserve Bank of St. Louis. IP is seasonally-adjusted and for both series I use the latest vintage.[7] In this paper, I focus mainly on a quarterly frequency.[8] Throughout, I present select results for the monthly frequency as a check of robustness.

In order to test whether the state variables predict macroeconomic activity, I conduct long-horizon predictive regressions, which are common in the time-series predictability literature:

$$y_{t,t+S} = a_S + b'_S z_t + e_{t,t+S}, \tag{5}$$

where $y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right)$ $(\sum_{s=1}^{S} CF_{t+s})$ measures macroeconomic growth over S periods; z_t is a set of candidate state variables and $e_{t,t+S}$ is a forecasting error with zero mean conditional on z_t. The sign

[7] Results for the real-time vintage series are similar.

[8] Quarterly IP compounds monthly growth rates, whereas quarterly CF is a 3-month moving average.

of the slope coefficients in b_S indicates whether a given state variable forecasts positive or negative changes in macroeconomic activity. In the ICAPM of Equation (2), this sign determines the sign of the risk premium for exposure to that state variable in the cross-section. Similarly, Maio and Santa-Clara (2012) conduct these regressions with aggregate stock market returns on the left-hand side to test the ICAPM of Merton (1973). The original sample is 1962.Q1 to 2011.Q4, which corresponds to the time span used in most empirical asset pricing studies of the cross-section.

In the main analysis, z_t includes three popular state variables that are known to predict returns in various asset classes: the Dividend Yield (DY) of the CRSP value-weighted stock portfolio (the ratio of dividends over the last 12 months and the current level of the index), the Default Spread (DS) between the yield of long-term corporate BAA and AAA bonds (both monthly averages) and the Term Spread (TS) between the yield of the ten and one year government bond (both observed at month-end).[9] Data on bond yields are from the FRED® database of the Federal Reserve Bank of St. Louis.

In a number of studies, e.g., Petkova (2006) and Kan et al. (2012), the Risk-Free rate (RF) is included as fourth state variable. I find that RF is largely redundant in the presence of TS and therefore exclude it in the main analysis. The exclusion of RF is attractive also, because it allows me to estimate one beta less per stock, per period. I present results for RF as a robustness check throughout the paper. In this

[9] Gilchrist and Zakrajsek (2012) propose an alternative measure of default risk that is a better predictor of macroeconomic aggregates, based on the cross-section of corporate bond yields. I discuss the pricing of this alternative to DS in a robustness check.

robustness check, I also present results for two competing models. First, the model of Campbell and Vuolteenaho (2004), which includes TS, the price-earnings ratio (PE) and the value spread (VS).[10] Second, the model of Koijen et al. (2013), which includes the Cochrane and Piazzesi (2005) bond market factor (CP) and the level factor (LVL).[11]

B Cross-sectional regressions

In order to test the pricing model in Equation (4), I run Fama and MacBeth (1973) cross-sectional regressions of individual stock returns on conditional betas with respect to innovations in the state variables. First, Litzenberger and Ramaswamy (1979) and Ang et al. (2011) argue that firm-level tests may be more efficient than portfolio-level tests, because the wider dispersion in betas, should more than make up for the larger degree of noise in the estimated betas when estimating risk premiums. Second, conditional exposures ensure that the investor can apply these strategies in real-time and are consistent with extant evidence that firm-level exposures are time-varying. This subsection describes the two main ingredients for these regressions: state variable innovations and betas. Finally, I interpret the cross-sectional regression as a portfolio strategy.

Innovations I adopt the approach of Campbell (1996) and assume the state variables follow a first-order Vector Auto-Regressive process

[10] PE is the log ratio of the price of the S&P 500 index to a ten-year moving average of earnings. VS is calculated from six Size and Book-to-market sorted portfolios as in Campbell and Vuolteenaho (2004).

[11] CP is the fitted value from a regression of an average of excess bond returns on forward rates. LVL is the first principal component of the one- through five-year Fama-Bliss forward rates, which is highly correlated to RF (the correlation coefficient equals 0.97 at both frequencies). For details on the construction of both series see Cochrane and Piazzesi (2005).

($VAR(1)$).[12] To be consistent with previous work, I use the CRSP value-weighted stock market return as proxy for the market portfolio. To ensure the betas are fully conditional, the VAR uses only historical data in period t. Thus, I estimate $y_\tau = A_0^t + A_1^t y_{\tau-1} + e_\tau^t$, where the superscript t indicates that $\tau = 1,..,t$. Moreover, $y_t = (r_{m,t}, z_t')'$, where z_t collects the state variables, such that $z_t = (DY_t, DS_t, TS_t)'$ in the main analysis. Following Petkova (2006), the innovations e_τ^t are orthogonalized from the market return $r_{m,\tau}^t$ and scaled to have the same variance as $r_{m,\tau}^t$. This orthogonalization is particularly important for DY. When the VAR is estimated over the full sample, the correlation between the excess market return and innovations in DY is -0.89. The innovations are not orthogonalized from each other, because (i) their correlations are below 0.20 and (ii) this could add additional noise through the arbitrary ordering of the variables.[13] The transformed innovations in the state variables, used as risk factors in the asset pricing model in period t, are denoted $\varepsilon_{z,\tau}^t = (\varepsilon_{DY,\tau}^t, \varepsilon_{DS,\tau}^t, \varepsilon_{TS,\tau}^t)'$.

Betas I use all ordinary common stocks traded on NYSE, AMEX and NASDAQ (excluding firms with negative book equity). To be consistent with previous work, I exclude financial firms. Although financials are potentially useful for hedging, their inclusion does not meaningfully alter the main conclusions. Furthermore, I require that at least four out of the last five years of returns are available for a stock to be included. I use a weighted least-squares regression over

[12] The results are qualitatively similar for innovations from a $VAR(2)$, an $AR(1)$ and for first-differences in the state variables. Select results from these robustness checks are discussed below.

[13] Lioui and Poncet (2011) show that results for a VAR-ICAPM are sensitive to the orthogonalization procedure. This sensitivity is particularly strong for RF as is shown in Section C.C.

all observations $\tau = 1, ..., t$ and shrink these betas as suggested in Vasicek (1973). These modifications to the usual rolling-window beta are important, because exposures to non-traded factors tend to be small and hard-to-estimate.[14] The expanding window ensures that we use as much information as possible, whereas an exponential decay in the weights ensures timeliness of the estimated betas. Thus, for each stock $i = 1, ..., N_t$ the WLS-estimator of $\delta_{i,t}$ follows from solving

$$\underset{\alpha_{i,t},\beta_{i,m,t},\delta_{i,t}}{\arg\min} \sum_{\tau=1}^{t} K(\tau) \left(r_{i,\tau} - \alpha_{i,t} - \beta_{i,m,t} r_{m,\tau} - \delta_{i,t}^{'} \varepsilon_{\tau}^{t} \right)^2, \tag{6}$$

$$\text{with weights } K(\tau) = \frac{\exp(-|t-\tau|\ h)}{\sum_{\tau=1}^{t} \exp(-|t-\tau|\ h)}.$$

With $h = \frac{\log(2)}{20}$ in case of quarterly data (and $h = \frac{\log(2)}{60}$ in case of monthly data), the half-life converges to 5 years for large t. Next, I perform the Bayesian transformation

$$\widehat{\delta_{i,k,t}^{v}} = \widehat{\delta_{i,k,t}} + \frac{var_{TSD}(\widehat{\delta_{i,k,t}})}{\left(var_{TSD}(\widehat{\delta_{i,k,t}}) + var_{CSD}(\widehat{\delta_{i,k,t}}) \right)} \left(mean_{CSD}(\widehat{\delta_{i,k,t}}) - \widehat{\delta_{i,k,t}} \right), \tag{7}$$

where the subscripts TSD and CSD denote means and variances taken over the time-series dimension τ and cross-sectional dimension i, respectively. In this way, $\widehat{\delta_{i,k,t}^{v}}$ is a weighted average of the estimated beta and the cross-sectional average beta, where the former receives a larger weight when it is estimated more precisely. Among others, Elton et al. (1978) and Cosemans et al. (2012) show that this adjustment improves forecasted exposures. For the state variables studied

[14] The main results are qualitatively similar, but weaker for the more noisy rolling-window betas.

in this paper, the cross-sectional average of the fraction in Equation (7) is about 0.30. Thus, the average amount of shrinkage in this paper is similar to Bloomberg's estimate for market betas. From this point forward, all results are based on these adjusted exposures, simply denoted $\delta_{i,k,t}$. Accounting for a burn-in period of five years when estimating beta, the sample period amounts to a total of 179 quarterly (537 monthly) cross-sectional regressions from 1967Q2 to 2011Q4.

Mimicking portfolio interpretation In each period t, I estimate risk premiums $\lambda_t = (\lambda_{m,t}, \lambda'_{z,t})'$ by running Fama and MacBeth (1973) cross-sectional regressions for $i = 1, ..., N_t$:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}. \tag{8}$$

As shown in Fama (1976), this cross-sectional regression implicitly defines a strategy that is the purest way to hedge state variable risk, as each element of λ_t can be interpreted as the return on a zero-investment portfolio that has a conditional beta of one with respect to the factor of interest and a conditional beta of zero with respect to all other factors. This result follows from post-multiplying the portfolio weights for state variable k, i.e., the $k+2$-th row of $(B'_tB_t)^{-1}B'_t$ (where B_t has typical row $B_{i,t} = (1, \beta_{i,m,t}, \delta'_{i,t})$), with B_t itself. In the following, I present select for a cross-sectional regression that restricts the intercept to zero ($\lambda_{0,t} = 0$), as dictated by the ICAPM in Equation (2). In this case, the unit exposure portfolio strategy is not restricted to be zero-investment anymore.

Note, because $B_{i,t}$ contains pre-ranking betas, which are noisy, the post-ranking exposure to factor k is likely smaller than one (and to the other factors unequal to zero). To ensure that the state variables are not useless factors in the sense of Kan and Zhang (1999), I test whether the cross-sectional regression portfolios are exposed ex-post to the respective state variable innovation in Section D.

The cross-sectional regression portfolio can be thought of as simple, out-of-sample proxy of the maximum correlation mimicking portfolio of Breeden et al. (1989). This portfolio cannot be estimated, because there are more stocks than time-series observations. The alternative, using a small set of portfolios as base assets, is unattractive as long as we are uncertain that these portfolios span the cross-section or when these portfolios have a strong factor structure (Lewellen et al. (2010)). For instance, Maio and Santa-Clara (2012) find differences, in both absolute value and sign, between risk premiums estimated using 25 Size and Book-to-Market portfolios and 25 Size and Momentum portfolios.

As a benchmark, I also present results for both market value- and equal-weighted High minus Low spreading portfolios (HLSP) in Section D, which are split at the quintiles of ranked exposures. These HLSP's are likely more interesting from a practical point of view, because they require an investment in a subset of the available stocks only.

C Time-series and cross-sectional consistency

This section presents the main test of this paper and asks whether the risk premium for exposure to state variable risk in the cross-section of individual stocks is consistent with how this state variable predicts macroeconomic activity in the time-series. First, I present both time-series and cross-sectional regressions for the three most popular state variables in the empirical asset pricing literature, that is, the Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). Subsequently, I ask whether the main conclusions from this exercise are general to a broader set of ICAPM-motivated state variables.

A Do state variables predict macroeconomic activity?

Time-series predictability is a necessary condition for a state variable to be priced in the ICAPM of Equation (2). When there are multiple state variables, we should focus on the marginal predictive role of each variable, conditional on all other variables. For this reason, Table I presents both single and multiple regressions of current and future Industrial Production Growth (IP) or Chicago Fed National Activity Index (CF) on the state variables, where all variables are standardized to accomodate interpretation.[15] I use as forecasting horizon $S = 0$, 1, 2, 4, 8 and 20 quarters in Panel A and $S = 0$, 1, 6, 12, 24 and 60 months in Panel B. I use both Newey and West (1987) and Hansen and Hodrick (1980) asymptotic standard errors with S lags to correct for the serial correlation in the residuals induced by the overlapping data.

Let us initially focus on the single regressions for IP at the quarterly frequency. First, DY predicts current and next quarter IP with a marginally negative coefficient that translates to an R^2 of about 3%,

[15] R^2 is not reported for the single regressions, because it is equal to the square of the estimated regression coefficient.

but does not predict at longer horizons. Similarly, DS predicts current and short-term future IP with a negative sign. The coefficient is significant up to two quarters ahead and translates to an R^2 that falls from 20% for $S = 0$ to 6% for $S = 2$. In contrast, TS predicts short- and long-term future IP with a positive sign. The coefficient is significant up to eight quarters out and translates to an R^2 increasing from 3% for $S = 1$ to 13% for $S = 8$. In unreported results, I find that the TS coefficient is positive and significant up to $S = 18$, but peaks around $S = 8$.

In multiple predictive regressions, the three variables jointly explain about 15% to 20% of the variation in both short- and long-term future IP. The coefficients for DS and TS are consistent in sign with, but strenghten relative to the single regressions. DS is the most important predictor of current and short-term future IP, with a negative coefficient that remains significant up to $S = 8$. TS is the most important predictor of long-term future IP, with a positive coefficient that is significant up to $S = 20$. In the presence of DS and TS, DY turns out to be a positive predictor of long-term future IP, in contrast to the single regression. The DY coefficient for $S > 8$ is economically large above 0.30, but typically insignificant, however. In the remaining blocks of Panel A, we see that these results are robust for CF. Moreover, Panel B demonstrates that these conclusions largely extend at the monthly frequency.

In terms of the model, these predictive regressions clearly indicate what the sign of the risk premium for exposure to DS and TS must be. DS predicts short-term future economic activity with a negative sign, consistent with evidence in Chen (1991) and Gilchrist and Zakrajsek (2012). In contrast, TS predicts (long-term future) economic activity with a positive sign. In fact, a negative TS has preceded all US recessions since the 50s, with only one false signal (see, e.g., Adrian and Estrella (2008)). Thus, it is natural to interpret an increasing DS as bad news and an increasing TS as good news, such that their risk premiums must be negative and positive, respectively.[16]

In contrast, the regressions do not allow for a clear-cut interpretation of an increasing DY as either good or bad news. On one hand, DY predicts positive changes in long-term future macroeconomic activity in multiple regressions, which suggests the risk premium must be positive. On the other hand, these positive long-term coefficients are (i) poorly estimated, (ii) insignificant in single regressions, where the short-term coefficients are actually marginally significant with the opposite sign, and (iii) sensitive to the chosen sample period. For instance, DY predicts current and short-term future macroeconomic activity with a marginally negative coefficient pre-1990 in multiple regressions, consistent with Chen (1991).[17]

Finally, note that DY, DS and TS all predict positive stock market returns in Maio and Santa-Clara (2012), such that the ICAPM of Merton (1973) implies that all three risk premiums are positive. Next, I estimate risk premiums in the cross-section of individual stocks to

[16]In unreported results, I run predictive regressions for realized variance in stock and bond markets as well as consumption. The results are very much consistent with the interpretation of an increasing DS as bad news, because it predicts realized variance with a positive sign and consumption with a negative sign, and an increasing TS as good news, because it predicts realized variance with a negative sign and consumption with a positive sign. In fact, in absolute magnitude the coefficients for consumption and IP are similar.

[17]The results for DS and TS are qualitatively similar pre- and post-1990. These results are available upon request.

evaluate these two competing sets of predictions.

B Is exposure to state variable risk priced?

Table II presents results for the Fama and MacBeth (1973) firm-level cross-sectional regressions of Equation (8). For the periodically estimated risk premiums $\lambda_t = (\lambda_{m,t}, \lambda'_{z,t})'$, I present the annualized unconditional average: $\widehat{\lambda} = \frac{1}{T}\sum_t \widehat{\lambda}_t$, which is my estimate of the state variable risk premium, as well as the Fama and MacBeth (1973) t-statistic, which uses the time-series standard deviation of the estimate. Also, I present the average cross-sectional $R^2 = \frac{1}{T}\sum_t R_t^2$. Consistent with the long-horizon regressions in Table I, I consider a two-factor model that includes DY, DS or TS next to MKT as well as a joint four-factor model.

Let us initially focus on the quarterly regressions in Panel A. In the two-factor models, only the DS risk premium is significant at -8.15% ($t = -3.24$). The TS risk premium is non-negligible economically at 2.85%, but insignificant ($t = 1.34$), whereas the DY risk premium is essentially zero. In the four-factor model, which is most relevant in the presence of multiple state variables, the risk premium for DS and TS are large and significant at -6.50% ($t = 2.75$) and 5.77% ($t = 3.20$), respectively. In both cases, this risk premium is consistent with the predictive regressions of Table I and the consequent interpretation of an increasing DS as bad news and an increasing TS as good news. Again, the DY risk premium is small and insignificant, which is consistent with the absence of a robust relation between DY and macroeconomic activity.

In the joint model, the average cross-sectional R^2 equals 3.71%, which is typical for this exercise (see, e.g., Fama and French (2008)). Throughout, the MKT risk premium is positive, but small and insignificant at about 2%. When we restrict the intercept to zero, the MKT risk premium changes dramatically to a large and significant 7%. This result is common in the literature. When the intercept is restricted to zero, MKT beta is used to fit the equal weighted average return of the tests assets in the cross-sectional regression, because this beta is centered around one. This estimate is close to the sample average return on the MKT portfolio and implies an economically plausible relative risk aversion coefficient of about 2 in the ICAPM of Merton (1973) and Campbell (1996).[18] Moreover, when we restrict the intercept to zero, the TS risk premium is larger by about 1% and as a result marginally significant in the two-factor model at 3.74% ($t = 1.72$).

The estimates are quantitatively similar at the monthly frequency in Panel B. For instance, in the four-factor model, the risk premiums for DS and TS are large and significant at -5.28% ($t = -2.21$) and 5.49% ($t = 2.69$), respectively, whereas the risk premium for DY remains insignificant at 1.54%. Moreover, these results are qualitatively robust in Panel C, where we estimate exposures with respect to first-differences in the state variables instead of $VAR(1)$-innovations.[19] Quantitatively, two differences stand out, however. First, the risk pre-

[18] To be precise, because the state variable innovations are orthogonalized from MKT, the estimated relative risk aversion coefficient is the ratio of the estimated MKT risk premium and the variance of the MKT portfolio, that is, $\frac{0.07/4}{0.09^2} = 2.16$.

[19] Further, the Internet Appendix demonstrates that the results are both qualitatively and quantitatively similar for $VAR(2)$-innovations in the state variables.

mium for TS is smaller by about 2%, but typically remains significant. Second, the DY risk premium turns negative and significant when excluding the intercept. The latter result is solely due to the fact that simple changes in DY are strongly correlated with the MKT return, which is why I have orthogonalized the $VAR(1)$-innovations from the MKT as in Campbell (1996).

To sum up, I estimate risk premiums for DY, DS and TS in the cross-section of individual stocks that are largely consistent with the ICAPM derived in Section A. DS and TS are robust predictors of macroeconomic activity and their respective risk premiums are large and significant around -6% and +6%, respectively.[20] Throughout the DY risk premium is positive, but insignificant, which is consistent with how DY predicts macroeconomic activity. On one hand, DY predicts long-term future activity with a positive sign in multiple regressions. On the other hand, this relation is poorly estimated and not robust across specifications and sample periods. In fact, when I split the sample in two, the average DY risk premium equals -1.79% pre-1990 and 4.24% post-1990. This increase is consistent with the finding that DY predicts negative changes in macroeconomic activity in multiple regressions pre-1990, but positive changes over the full sample.

These firm-level risk premium estimates compare to previous portfolio-level estimates as follows. First, the DS risk premium is also negative among portfolios, but insignificant, which suggests this risk premium is indeed estimated more efficiently using individual stocks. Second,

[20] The Internet Appendix demonstrates that the alternative measure of default risk in Gilchrist and Zakrajsek (2012) is priced similar to DS with a quarterly risk premium of -5.89% relative to -5.83% for DS over the period 1978.Q2 to 2010.Q3, which is dicated by data availability. Moreover, the correlation over time between the two risk premiums is 0.75. This finding suggests that DS contains a large chunk of the information relevant for pricing in the alternative measure.

the estimated DY risk premium is typically negative and insignificant among portfolios. As Maio and Santa-Clara (2012) note, the sign of the portfolio-level estimate is inconsistent with the ICAPM of Merton (1973), because both DS and DY predict positive stock market returns. Third, Maio and Santa-Clara (2012) find that the sign of the TS risk premium is sensitive to the choice of portfolios. A positive TS risk premium is consistent with both versions of the ICAPM, however, as TS predicts both positive stock market returns and macroeconomic activity.

C Alternative ICAPM-motivated state variables

Having established that the time-series is consistent with the cross-section in case of DY, DS and TS, this subsection asks whether this consistency is general to a broader set of ICAPM-motivated state variables. For this exercise, I focus on four alternative models inspired by Maio and Santa-Clara (2012) as described in Section B. First, I analyze a three-factor model that replaces TS with RF, the 3 month t-bill rate. Second, I include RF next to DY, DS and TS. Here, I first orthogonalize RF from TS (denoted RF|TS), to alleviate multicollinearity concerns due to a high correlation between the levels of these variables: -0.62, but even more so their (full sample) $VAR(1)$-innovations: -0.82. Third, I consider the model of Campbell and Vuolteenaho (2004), which includes TS, the price-earnings ratio (PE) and the value spread (VS). Finally, I analyze the model of Koijen et al. (2013), which includes the Cochrane and Piazzesi (2005) bond market factor (CP) and a term structure level factor (LVL).

Time-series Table III presents the time-series regressions of IP and CF on the alternative state variables, similar to Table I. For this exercise, I focus solely on the quarterly frequency, because results at the monthly frequency are largely similar.[21] Moreover, I focus solely on the coefficients for the new state variables, because the evidence for DY, DS and TS is largely unchanged from Table I. In this table, ***, ** and * indicate significance at the 10%, 5% and 1%-level, respectively, using the more conservative Hansen and Hodrick (1980) asymptotic standard errors with S lags. To conserve space, I report results only for multiple regressions and three horizons $S = 1, 4, 8$.

In Model (1), RF predicts four and eight quarter ahead IP and CF with a significant negative coefficient. In unreported results, I find that this predictability is significant from $S = 3$ to $S = 24$, and peaks at $S = 8$. This pattern is similar to TS and consistent with evidence in Chen (1991) and Estrella and Hardouvelis (1991), among others. These authors argue that higher real rates today imply low current investment opportunities and lower output in the future. Thus, I predict a negative risk premium for exposure to RF, because high RF exposure stocks are attractive as a hedge.

Also, consistent with Chen (1991) and Estrella and Hardouvelis (1991), RF does not contain much independent information about future macroeconomic activity relative to TS. In Model (2), the magnitude of the negative coefficient for RF|TS is about half what it is in Model (1) for $S = 4$ and 8. In case of CF, these coefficients are practically zero. Thus, I conclude that the risk premium for RF|TS

[21] These results are presented in the Internet Appendix.

should be zero.

In Model (3), VS predicts next-quarter IP with a negative coefficient that is significant at the 5%-level. VS is more important in predicting CF, with a negative coefficient that is significant at the 1%-level for $S = 1$ and 4. In fact, in unreported results I find that VS predicts future CF with a negative and significant coefficient up to $S = 7$. This predictability is consistent with Campbell and Vuolteenaho (2004), who find that shocks to VS are an important component of market cash flow news, with a negative correlation between the two. Indeed, if a positive shock to VS predicts lower macroeconomic activity, one would expect market cash flows (dividends) to fall. In contrast, PE only predicts one quarter ahead IP with a marginally positive coefficient, whereas this variable is insignificant at all three horizons in case of CF. In single regressions, PE is also largely insignificant, whereas VS remains an important negative predictor of CF, in particular. Consequently, the risk premium for exposure to VS should be negative, whereas exposure to PE risk should not be priced.

In Model (4), CP predicts predicts eight quarter ahead macroeconomic activity with a positive coefficient that is significant at the 1%-level, consistent with Koijen et al. (2013). For both IP and CF, this predictability is (marginally) significant from about one to five years into the future, with a peak around three years. The coefficient for the LVL factor is negative at all three horizons and for both IP and CF, which is consistent with RF. However, there is likely not enough information for an investor to use this variable to hedge against time-varying investment opportunities, because it is only marginally significant at $S = 8$ in case of IP. Consequently, I predict a positive risk premium for CP, whereas exposure to LVL risk should not be priced.

Cross-section Table IV presents firm-level Fama and MacBeth (1973) cross-sectional regressions for the alternative sets of state variables (with conditional betas estimated as in Equations (6) and (7)). The structure is similar Table II and I present unconditional average annualized risk premiums, the corresponding Fama and MacBeth (1973) t-statistics (in parentheses), and the average cross-sectional R^2.

In Model (1), the risk premium for RF is negative, as predicted, at a marginally significant -3.64% ($t = -1.77$). The inclusion of RF instead of TS has little effect on the risk premiums for DY and DS. A negative RF risk premium is consistent in sign with previous portfolio-level evidence with one caveat: RF has little to add to a model that already includes TS. Indeed, in Model (2), RF|TS is insignificant at 1.43%, consistent with the fact that RF|TS does not predict macroeconomic activity in the presence of TS.[22]

In Model (3), the risk premium for exposure to innovations in PE is insignificant at 1.67%, as hypothesized. In contrast, exposure to VS is priced at an economically large and significant -5.23 ($t = -2.56$). These findings are consistent with evidence in Campbell and Vuolteenaho (2004) in that shocks to VS (PE) are an important negative component of market cash flow news (market discount rate news), whereas the risk premium for exposure to market cash flow news is large relative to the risk premium for exposure to mar-

[22] The reverse is not true: TS|RF remains significant in the cross-sectional regression when RF is included already. The same result obtains for 25 Size and Book-to-Market portfolios. These results are available upon request.

ket discount rate news. In model (4), exposure to CP is priced at 4.21% ($t = 2.23$), which is consistent with the finding that CP predicts macroeconomic activity with a positive sign as in Koijen et al. (2013). In contrast to these authors, but consistent with the lack of a robust relation between LVL and future macroeconomic activity, I find that LVL is insignificant at 2.35%.[23]

These results are robust to restricting the intercept to zero. In this case, the MKT risk premium is again forced up to about 7%, whereas the risk premiums for RF, VS and CP are slightly larger in absolute value. Moreover, the results are largely similar at the monthly frequency. The main difference is that the risk premiums for VS and CP increase considerably to -8.63% ($t = -3.44$) and 5.85% ($t = 2.64$), respectively. Also, the Internet Appendix presents similar pricing evidence when exposure is measured with respect to first-differences or $VAR(2)$-innovations in the alternative state variables.

To sum up, I find that the risk premiums for innovations in the set of alternative state variables RF, PE, VS, CP and LVL are also consistent with whether or not their level is a robust predictor of macroeconomic activity in the time-series and, when it is, with the sign of the predictive relation. This result compares to Maio and Santa-Clara (2012) as follows. In case of RF, VS and CP the estimated risk premium has the same sign among portfolios, but is insignificant, which again suggests that using individual stocks is more efficient. In case of VS and CP, the sign is consistent with how each variables

[23] Because LVL and RF are highly correlated, I add LVL to DY and DS in a robustness check. In this setup, the LVL risk premium turns negative, but remains small and insignificant. These results are available upon request.

predicts stock market returns and therefore the ICAPM of Merton (1973). In contrast, the risk premium for RF is negative, whereas this variable predict positive market returns. Finally, the risk premiums for PE and LVL are similarly insignificant among portfolios, and as argued in Maio and Santa-Clara (2012), this finding is inconsistent with the fact that these variables do predict stock market returns.

D Individual stock-based state variable mimicking portfolios

This subsection presents the portfolios implicit in the cross-sectional regression procedure in more detail. As a benchmark, I present results for market value-weighted and equal-weighted portfolios split at the quintiles of ranked values. First, I test whether each portfolio is exposed to the risk factor it is supposed to mimick ex post, which is a prerequisite for the portfolios to capture a risk premium and ascertains that the state variables are not useless factors in the sense of Kan and Zhang (1999). Next, I analyze whether the portfolios (i) load on stocks with certain characteristics and (ii) are costly to trade. Throughout, I focus on the quarterly frequency, because these portfolios mimick better, whereas quarterly rebalancing reduces transaction costs.[24] As before, I focus first on DY, DS and TS. Subsequently, I present outtakes of largely consistent results for the alternative state variables.

[24] Select results at the monthly frequency are described below. The complete set of results can be found in the Internet Appendix.

A Dividend Yield, Default Spread and Term Spread

Panel A of Table V presents post-ranking exposures $(\beta_m, \delta')'$ from the four-factor model $r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon^{Full}_{DY_t}, \varepsilon^{Full}_{DS_t}, \varepsilon^{Full}_{TS_t})' + u_t$ as well as the weighted cross-sectional average pre-ranking exposure within a portfolio. The innovations ε^{Full}_t are estimated with a single $VAR(1)$, where the residuals are orthogonalized from $r_{m,t}$ and scaled to have the same variance as $r_{m,t}$. For each state variable k, I present exposures for three mimicking portfolios: the cross-sectional regression portfolio (FMB) as well as a market value-weighted and an equal-weighted spreading portfolio ($HLMV$ and $HLEW$).[25]

In short, all strategies create a mimicking portfolio that is exposed to the relevant risk factor ex post. The typical mimicking portfolio is only exposed to the one state variable that it is trying to mimick. Moreover, we see a roughly monotonic pattern moving from High to Low among the long-only market-value weighted portfolios. The loadings are typically significant and smallest for $HLEW$ at about 0.10 and largest for FMB at 0.29, 0.32 and 0.17 in case of DY, DS and TS, respectively. The relative success of FMB in creating an ex post exposure could be due to the fact that it can exploit cross-sectional correlation between exposures to the factors that is stable over time. The difference between ex post exposures and ex ante exposures, which are about one for all strategies, is due to imperfect prediction of the betas. This finding is common in out-of-sample exercises with non-traded factors. Nevertheless, the ex-post exposures are economically meaningful, translating to incremental quarterly returns ranging from

[25] I do not present results for the cross-sectional regression portfolio where the regression restricts the intercept to zero, because this portfolio is not zero-investment.

1.5% to 2.8% in case of FMB for a standard deviation increase in the risk factors. Thus, I conclude that these state variables are not useless factors.

The remaining columns of Panel A present annualized unconditional average return, standard deviation and Sharpe ratio. First, the average returns for $HLMV(DY)$ and $HLEW(DY)$ are similarly small and insignificant as $FMB(DY)$, suggesting again that DY risk is not priced. In contrast, DS risk is rewarded with a consistent negative premium. In case of $HLEW(DS)$, the risk premium is slightly smaller than, but similarly significant as $FMB(DS)$ at -4.59% ($t = -2.37$) versus -6.56% ($t = -2.75$). The absolute Sharpe ratio for these two strategies is large relative to the aggregate stock market at 0.35 and 0.41 relative to 0.30. The risk premium is insignificant in case of $HLMV(DS)$, however, which is suggestive of a Size effect. Finally, TS risk is rewarded with a consistent positive risk premium. The risk premiums are large and significant in all weighting schemes at over 4.90% per annum, which translates to Sharpe ratios ranging from 0.34 for $HLMV(TS)$ to 0.54 for $HLEW(TS)$.

At the monthly frequency, these results are largely similar for DY and TS, in which case the post-ranking exposures are only slightly smaller. In case of DS, the post-ranking exposures are positive, but insignificant, however. The presence of a Size effect is even more evident at this frequency, given large and significant negative DS risk premiums for $HLEW(DS)$ and $FMB(DS)$, but an insignificant positive risk premium for $HLMV(DS)$. This variability is perhaps unsurprising given that these portfolios are not strongly exposed ex post to DS risk in the first place.

Panel B of Table V describes the DY, DS and TS mimicking portfolios in terms of various characteristics. In each period, Size ($ billion), Book-to-Market and Momentum are weighted cross-sectional averages, whereas HH is a Herfindahl-index that sums squared portfolio weights ($\sum_i w_{i,t}^2$) and Turnover (annualized) is the amount of trading required to rebalance.[26] For $HLMV$ and $HLEW$, Turnover is calculated as

$$\frac{\sum_i \left| w_{i,t-1} \left(\frac{1}{2} \sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right| \right) - w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}{\sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}. \tag{9}$$

The numerator sums all absolute changes in the portfolio weights from the instant before rebalancing to the instant after, where the latter is scaled to ensure that the long and short position grow equally over time. The denominator scales by the size of the portfolio. For FMB, the total long and short position do not equal one dollar and vary over time. To ensure that trading keeps the pre-ranking beta equal to one, Turnover is calculated as

$$\frac{\sum_i \left| w_{i,t-1} - w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}{\sum_i \left| w_{i,t-2} \left(1 + r_{i,t-1}\right) \right|}. \tag{10}$$

To start, note that none of the strategies consistently loads on winners or losers and let us focus on $HLEW$, because this weighting scheme presents results that are typical and most comparable to pre-

[26] Book-to-Market (BM) is calculated in June as the ratio of the most recently available book-value of equity in Compustat (assumed to be available six months after the fiscal year-end) divided by Market Capitalization from CRSP (Size) at previous year-end. Momentum is defined as $\prod_{j=4}^{1} (1 + r_{i,t-j})$ and $\prod_{j=12}^{2} (1 + r_{i,t-j})$ at the quarterly and monthly frequency, respectively.

vious work.[27] First, high DY exposure stocks are smaller and have marginally higher Book-to-Market ratios. Second, Size and Book-to-Market are also significant for DS mimicking portfolios at 0.91$ billion and -0.36, respectively. This Size effect is consistent with Perez-Quiros and Timmermann (2000), who argue that small firms are more vulnerable to variation in credit market conditions over the business cycle, such that an increasing DS signals higher discount rates for smaller stocks. Since low DS beta stocks are also volatile, one can consider them "speculative" in the sense of Baker and Wurgler (2012). Similarly, because high Book-to-Market is indicative of relative distress (Fama and French (1995)), a negative relation with DS risk is natural. Third, high TS exposure stocks are smaller by 1.29$ billion, whereas their Book-to-Market ratio is higher by 0.17. Both characteristics are consistent with Petkova (2006) and Hahn and Lee (2006). A possible explanation is that small firms are marginal firms and therefore more sensitive to news about the business cycle (Chan and Chen (1991)). Further, Cornell (1999), Campbell and Vuolteenaho (2004) and Da (2009), among others, argue that value stocks are low duration assets, such that when an increasing TS signals higher discount rates on long-term assets, value will outperform growth contemporaneously.

In unreported results, I find that Book-to-Market is monotonically related to pre-ranking exposures to DY, DS and TS. In contrast, Size presents an inverted U-shape, because small stocks have more extreme betas. I conclude that if the characteristics Size and Book-to-Market explain the cross-section of expected returns completely, one would

[27] Note, Size is extreme in case of $HLMV$, because this strategy implicity squares market values.

expect an unconditional risk premium that is positive for DY and TS, but negative for DS. In Section E, I test whether these benchmark characteristics are able to capture the risk premiums for DS and TS consistent with this hypothesis.

In terms of transaction costs, the $HLMV$ portfolio is likely most attractive. This portfolio invests only in a subset of the available stocks, whereas larger stocks are more liquid. Also, the Herfindahl-index suggests that this portfolio is most concentraded. In terms of concentration, FMB is similar to $HLEW$, which suggest that the former is not requiring an investor to take extreme positions. Rather, FMB requires the investor to take many small positions. Nevertheless, transaction costs are unlikely to completely wipe out the average returns for either of these strategies. In particular, I find that average annual Turnover is about 1.6 for all strategies. This figure implies that an investor who is long and short one dollar and rebalances quarterly, will trade 3.2 dollars per year.[28] Assuming a conservative average quoted half-spread of 25 basis points, these trades add up to transaction costs of about 80 basis points (see, e.g., Chordia et al. (2011) and Hendershott et al. (2011)). As a benchmark, I calculate the amount of trading required to construct comparable portfolios for exposures to SMB and HML as well as for the characteristics Size and Book-to-Market. For these strategies, transaction costs are lower, but only by about 30%. On the other hand, for comparable Momentum strategies, the required amount of trading is larger by over 100%.

[28] Rebalancing the portfolios monthly increases the amount of trading by about 30%. Rebalancing the portfolios only at the end of the year rougly halves the amount of trading required and leaves all other results largely unchanged.

B Alternative ICAPM-motivated state variables

This subsection compares the unconditional performance of the three mimicking portfolios ($FMB, HLMV$ and $HLEW$) for the alternative state variables and asks whether these portfolios are exposed ex post. To conserve space, Table VI presents results only for the quarterly frequency and excludes the second model with DY, DS, TS and RF|TS.[29] Moreover, I do not analyze the mimicking portfolios for DY, DS and TS here, because these results are largely similar to Table V.

First, the risk premiums for RF, VS and CP are consistent in sign over the three strategies. In case of RF, the three risk premiums are significant and range from -6.34% for $HLEW(RF)$ to -3.64 for $FMB(RF)$. In case of VS and CP, there is more variation in absolute magnitude, which is suggestive of a Size effect that is further explored in Section E. The risk premiums are insignificant in case of $HLMV$, but significant otherwise at -3.79% (-5.23%) and 2.98% (4.21%), respectively, in case of $HLEW$ (FMB). Second, average returns are small and insignificant across the board for mimicking portfolios of innovations in PE and LVL.

To sum up, I find that the cross-sectional risk premiums for the alternative factors are robust in portfolio sorts. In case of RF, VS and CP, the various strategies typically obtain Sharpe ratios that are in the same order of magnitude as the aggregate stock market. Moreover, in unreported results, I find that the required amount of trading to execute these strategies is similar to DS and TS, such that transaction costs are unlikely to eradicate these average returns completely.

[29] Results at the monthly frequency can be found in the Internet Appendix.

These conclusions come with the caveat that the post-ranking exposure of these mimicking portfolios to the relevant factor is not always significant at the quarterly frequency. The exposures are consistently positive, however. Moreover, in the Internet Appendix, I show that post-ranking exposures are typically larger at the monthly frequency, whereas the risk premiums are largely similar.[30]

In unreported results, I find that these portfolios load distinctively on the characteristics Size and Book-to-Market, which is similar to DS and TS. To be precise, RF (VS and CP) portfolios demonstrate a large cap (small cap) tilt, whereas RF and VS (CP) portfolios demonstrate a Growth (Value) tilt. To analyze whether the state variables contain independent information for the cross-section of expected returns, the next section includes these characteristics (and the factors SMB and HML derived from them) in cross-sectional regressions.

E Relation to the Fama and French (1993) factors

This section analyzes how the state variable risk premiums relate to both the Fama and French (1993) factors (SMB and HML) and their underlying characteristics (Size and Book-to-Market). In this way, I respond to (i) Fama and French (1993, 1996), who appeal to the ICAPM for theoretical justification, (ii) Petkova (2006) and Hahn and Lee (2006), who argue that innovations in similar sets of state variables may substitute for SMB and HML, and (iii) the risk factor versus characteristic controversy discussed in Fama and French (1992), Daniel

[30]Koijen et al. (2013) perform a sort on rolling 60-month covariances with CP innovations in five market-value weighted groups. The high minus low return spread is 2.5%, but its t-statistic is not reported. In the monthly sort reported in the Internet Appendix, I find a similar risk premium of 3.08%.

and Titman (1997) and Chordia et al. (2012), among others.

A Dividend Yield, Default Spread and Term Spread

To start, Panel A of Table VII presents time-series regressions of the Fama and MacBeth (1973) cross-sectional regression risk premiums on the Fama and French (1993) three-factor model (FF3M) as well as the Carhart (1997) four-factor model (FFCM). Results are similar at the quarterly and monthly frequency, so let us focus on the former.

First, the portfolios $FMB(DY)$, $FMB(DS)$ and $FMB(TS)$ are exposed to SMB and HML in a manner that is largely consistent with the characteristics of Table V. In case of TS, a large and significant loading on HML captures its risk premium only partially, leaving an economically large and significant FF3M α of 4.20%, down from 5.79%. In contrast, a large part of the negative DS risk premium is captured by negative loadings on SMB, in particular, and HML, leaving an insignificant FF3M α of -2.89%, up from -6.50%. Adding MOM increases the α slightly for TS, but dramatically for DS, to an economically large, although insignificant FFCM α of -5.26%. In both the FF3M and FFCM, the DY risk premium remains small and insignificant.

In all, these time-series regressions suggest that the DS risk premium is a compensation for exposure to SMB and HML, whereas the TS risk premium is not. This suggestion does not mean, however, that exposures to DS and TS do not contain independent information about average returns in the cross-section. To answer this question, we must perform high-dimensional portfolio sorts or cross-sectional regressions. I follow the advice in Cochrane (2011) and run firm-level cross-sectional regressions, where the set of independent variables includes (i) conditional exposures to $VAR(1)$-innovations in the state variables DY, DS and TS, (ii) conditional exposures to the benchmark factors (MKT, SMB, HML and MOM), and (iii) characteristics (Size, Book-to-Market and Prior return).[31]

Using the procedure set out in equations (6) and (7), I start out regressing returns in each expanding window on an extended factor model that includes the benchmark factors SMB and HML. Then, in each period t, I estimate

$$\begin{aligned} r_{i,t+1} &= \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \lambda_{s,t}\widehat{\beta_{i,smb,t}} + \lambda_{h,t}\widehat{\beta_{i,hml,t}} \\ &\quad + \lambda'_{c,t}(Size_{i,t}, BM_{i,t})' + \upsilon_{i,t}. \end{aligned} \tag{11}$$

First, I restrict $\lambda'_{z,t} = \lambda'_{c,t} = 0$ to answer the question whether the benchmark factors SMB and HML are priced in the cross-section of individual stocks. Second, I restrict $\lambda'_{c,t} = 0$ to test whether exposures to DS and TS contain information about average returns that is orthogonal from SMB and HML. Third, I restrict $\lambda_{s,t} = \lambda_{h,t} = 0$ to test whether the state variable risk premiums are robust to the inclusion of characteristics, which is a simple test of model misspecification (Berk (1995) and Jagannathan and Wang (1998)). Note, however, that this test is biased in favor of characteristics, because these are measured without error.[32] Fourth, I estimate the full model in Equation (11). Finally, I estimate an extended model that includes both the momen-

[31] Following Chordia et al. (2012), Size is the natural logarithm of Market Capitalization and Book-to-Market (BM) is the natural logarithm of the Book-to-Market ratio winsorized at the 0.5th fractile. All characteristics are standardized cross-sectionally.

[32] Indeed, the errors-in-variables bias introduced by using estimated exposures ($\widehat{\delta_{i,t}}$) likely causes these regressions to *understate* the importance of intertemporal risk.

tum factor (MOM) and characteristic (Prior return). Throughout, I also present results for a model that restricts $\lambda_{0,t} = 0$.

Let us first consider the quarterly frequency in Panel B. In the FF3M, the risk premiums for SMB and HML are positive at 1.91% and 2.63%, respectively. Even though HML is significant at the 5%-level, this estimate is small relative to the factor's average return of 5%. The FF3M explains a similar amount of cross-sectional variation as the ICAPM-model in Table II at an R^2 of 4.24%. In fact, adding SMB and HML to this model has only a minor effect on the risk premiums for DS and TS, which remain large and significant at -5.58% ($t = 2.52$) and 4.20% ($t = 2.61$), respectively. Conversely, the risk premiums for SMB and HML do not change much relative to the FF3M either. These findings imply that DS and TS contain orthogonal information about average returns in the cross-section of individual stocks.

When substituting Size and Book-to-Market for exposures to SMB and HML, the two characteristics are significant at the 1%–level at -3.23 and 2.96, respectively. In the presence of these characteristics, DS exposures are driven out, leaving a small and insignificant DS risk premium of -1.77% ($t = -1.06$). In unreported results, I find that the same result obtains when including Size alone, which again suggests the DS risk premium is a Size effect. In contrast, TS survives and its risk premium remains large and significant at 4.28% ($t = 2.79$). In the full model, that includes both the benchmark factors and their underlying characteristics, the conclusions for DS and TS are largely similar. Moreover, exposures to SMB and HML are driven out, as expected.

These conclusions are robust when we restrict the intercept to zero. In this case, the risk premiums for the factors DS, TS, SMB and HML are slightly larger in absolute value, whereas the MKT risk premium is large and significant, as before. These conclusions are also robust at the monthly frequency in Panel C. The main difference is that the risk premiums for both DS and TS are slightly smaller in absolute value. In case of TS, the difference is small when restricting the intercept to zero. Without this restriction, the TS risk premium remains economically large, but is not always significant. Finally, these conclusions are largely unaltered in the model that also controls for exposures to MOM and PRET. The MOM risk premium is negative, however, which is consistent with the idea that this factor is not a compensation for risk.

To conclude, these cross-sectional regressions suggest DS is largely a Size effect in an ex ante sense. DS mimicking portfolios are long big stocks and short small stocks. As a result, the factor SMB, which loads on Size in the opposite manner, captures a large chunk of the DS risk premium in time-series regressions. Moreover, DS is driven out by the characteristic Size in cross-sectional regressions. In contrast, DS is not driven out by the inclusion of exposures to SMB.

Although, TS and HML are correlated risk factors, for instance, because TS mimicking portfolios load on Value stocks, the positive TS risk premium survives in both time-series and cross-sectional regressions.[33] Similar to SMB, HML is eradicated by its underlying

[33] Another indication that the TS risk premium is robust comes from running cross-sectional regressions within three Size, Book-to-Market or momentum groups, as in Fama and French (2008). I find that the TS risk premium is positive in all nine control groups at over 2.3% and significant at over 5% in seven (except among Big and low Book-to-Market stocks). These results are available

characteristic in cross-sectional regressions, however. These findings extend Petkova (2006) and Hahn and Lee (2006), who find that TS exposures contain orthogonal information (relative to HML and Book-to-market) in pricing a set of 25 Size and Book-to-Market portfolios, whereas DS exposures do not.

B Alternative ICAPM-motivated state variables

Table VIII is similar to Table VII, but focuses on cross-sectional regressions that ask whether the risk premiums for the alternative state variables are robust to the inclusion of SMB and HML (Model (I)) and, in addition, Size and Book-to-Market (Model (II)). I do not present time-series regressions to conserve space. In sum, these time-series regressions suggest that the risk premiums for RF and CP are captured largely by SMB and HML, similar to DS, whereas the risk premium for VS is not, similar TS.

First, exposures to SMB and HML do not fully drive out exposures to RF, VS and CP in cross-sectional regressions, which is similar to the case of DS and TS. In the quarterly regressions that include an intercept, the risk premiums for RF, VS and CP are economically large at about 3% in absolute value, although the estimate is only significant for VS. At the monthly frequency, the risk premiums for VS and CP strenghten and are significant at -7.06% and 3.43%, respectively.

Second, adding characteristics does not fully drive out RF exposures either. The RF risk premium is insignificant, though economically meaningful when including an intercept at -2.50% at both fre-

upon request.

quencies. Moreover, the monthly RF risk premium is significant in the specification that restricts the intercept to zero at -3.43% ($t = -2.00$). Although weaker, this pattern is similar to TS, which is perhaps unsurprising, because the two factors are correlated. Indeed, we find that TS|RF has little to add to a specification that already includes TS, even when including the benchmark factors and characteristics.

Although VS is driven out by characteristics at the quarterly frequency, it is not at the monthly frequency with a large and significant VS risk premium of -4.97% ($t = -2.24$) in the full model. Note, the monthly frequency is more relevant for this factor, because the ex post exposure to VS innovations is much larger at this frequency (see Table VI). In contrast, the risk premium for CP is small and insignificant when including characteristics at both frequencies. In unreported results, I find that the eradication of CP is driven quite equally by Size and Book-to-Market. Similarly, Koijen et al. (2013) find that covariances with CP innovations are correlated to Book-to-Market in the cross-section. Finally, for PE and LVL, the risk premiums remain small and insignificant in the presence of the benchmark factors and characteristics, which is similar to DY.

Thus, exposures to DS and CP are driven out unequivocally by characteristics, which suggests these state variables are not separate in an ex ante sense. In contrast, exposures to TS, RF and VS contain orthogonal information about the cross-section of expected returns. This result represents a success for the state variables, in particular, because these exposures are measured with error, whereas the characteristics are measured without error. Following this line of reasoning, a possible explanation for why DS and CP are not driven out by exposures to SMB and HML is that these benchmark exposures also suffer from measurement error.

F Conclusion

This paper follows a long tradition of papers at the intersection of macroeconomics and asset pricing. I find that the risk premiums for exposure to ICAPM-motivated state variables in the *cross-section* are consistent with how these variables forecast macroeconomic activity in the *time-series*. Following recent advice in the literature, I estimate the risk premiums using firm-level cross-sectional regressions and my evidence suggests this practice is indeed more efficient than using portfolios. This time-series and cross-sectional consistency is an important guard against factor fishing and is consistent with the idea that investors desire to hedge against adverse macroeconomic shocks. Thus, following advice in Cochrane (2005, Ch. 9), I identify "recession state variables".

My method consists of two elements. First, long-horizons regressions establish whether and how a candidate state variable predicts macroeconomic activity. Second, firm-level cross-sectional regressions establish whether a state variables is priced in a consistent manner. I consider four models with different state variables. First and foremost, I focus on a model with the Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). Next, I analyze whether and how the risk-free rate (RF) adds to this model. Third, I consider the model of Campbell and Vuolteenaho (2004), which includes TS, the price-earnings ratio (PE) and the value spread (VS). Finally, I consider the model of Koijen et al. (2013), which includes the Cochrane and Piazzesi (2005) bond market factor (CP) and a factor that measures the level of the term-structure (LVL).

I find that DS, RF and VS forecast negative changes in macroeconomic activity, TS and CP forecast positive changes, whereas DY, PE and LVL are not robust predictors. Consistent with this evidence, I estimate firm-level risk premiums that range from -6% to -3% for exposure to DS, RF and VS; that range from 4% to 6% for exposure to TS and CP; and, that are essentially zero for the remaining factors. The risk premiums for the priced state variables translate to Sharpe ratios in the same order of magnitude as the market portfolio: 0.30. I find similar pricing evidence among portfolio sorts, which suggests the state variable risk premiums are investible. Finally, I add to the debate on whether risk exposures or characteristics determine expected returns. I find that the benchmark factors SMB and HML do not eradicate the state variable risk premiums in cross-sectional regressions. Their underlying characteristics Size and Book-to-Market drive out DS, which is largely a Size effect, and CP, however. In contrast, RF, VS and especially TS do contain orthogonal information about the cross-section of expected returns.

A number of extensions come to mind. First, I have largely ignored how exactly the pre- and post-ranking betas vary cross-sectionally and over time, which is relevant for more advanced hedging strategies and portfolio optimization. Second, I leave open the question of how to determine the optimal out-of-sample hedge portfolio, which for most of the state variables in this paper likely loads on bonds. Relatedly, I have not analyzed whether the various ICAPM-models are able to price the cross-section of stocks and (government) bonds simultaneously, as in Koijen et al. (2013).

Table I: Do DY, DS and TS predict macroeconomic activity?
This table reports the results for single and multiple regressions of current and future industrial production growth (IP) and the Chicago Fed National Activity index (CF) on the Dividend Yield (DY), Default Spread (DS) and Term Spread (TS). Panel A uses quarterly data and considers horizons $S = 0, 1, 2, 4, 8, 20$; Panel B uses monthly data and considers horizons $S = 0, 1, 6, 12, 24, 60$. The original sample is 1962.Q1 to 2011.Q4, and S-1 observations are lost in each of the respective S-horizon regressions. All variables are standardized. The first block of results in each panel presents the single regressions, where I report the slope estimates b_S (which squares equal the regression R^2) and t-ratios using asymptotic Newey-West (in parentheses) and Hansen-Hodrick (in brackets) standard errors computed with S lags. The second block of results in each panel presents the multiple regressions, where I report slope estimates, t-ratios and R^2's.

$$y_{t,t+S} = b'_S z_t + e_{t,t+S} \text{ with } y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right) \text{ or } \sum_{s=1}^{S} CF_{t+s}$$

Panel A: Quarterly data

		Dividend Yield			Default Spread			Term Spread			
	S	b_S	$t_{S,NW}$	$t_{S,HH}$	b_S	$t_{S,NW}$	$t_{S,HH}$	b_S	$t_{S,NW}$	$t_{S,HH}$	R^2
					Single predictive regressions						
IP	0	-0.17	(-2.04)	[-2.05]	-0.45	(-5.70)	[-5.71]	-0.05	(-0.79)	[-0.79]	
	1	-0.19	(-1.73)	[-1.53]	-0.30	(-3.31)	[-2.97]	0.18	(2.04)	[1.89]	
	2	-0.16	(-1.34)	[-1.17]	-0.24	(-2.35)	[-2.09]	0.23	(2.37)	[2.03]	
	4	-0.06	(-0.48)	[-0.42]	-0.13	(-1.07)	[-0.98]	0.28	(2.67)	[2.34]	
	8	0.07	(0.46)	[0.40]	-0.04	(-0.31)	[-0.29]	0.36	(3.43)	[3.02]	
	20	0.15	(0.67)	[0.60]	-0.06	(-0.34)	[-0.31]	0.19	(1.21)	[1.30]	
CF	0	-0.11	(-1.31)	[-1.32]	-0.52	(-6.18)	[-6.20]	-0.11	(-1.81)	[-1.81]	
	1	-0.13	(-1.11)	[-0.95]	-0.35	(-3.12)	[-2.70]	0.12	(1.29)	[1.14]	
	2	-0.09	(-0.74)	[-0.62]	-0.28	(-2.22)	[-1.90]	0.17	(1.70)	[1.43]	
	4	0.00	(-0.02)	[-0.02]	-0.15	(-1.07)	[-0.95]	0.26	(2.44)	[2.12]	
	8	0.13	(0.78)	[0.68]	0.01	(0.10)	[0.10]	0.39	(4.14)	[4.23]	
	20	0.31	(1.49)	[1.75]	0.27	(1.78)	[1.81]	0.18	(1.39)	[1.62]	
					Multiple predictive regressions						
IP	0	0.06	(0.85)	[0.86]	-0.49	(-5.88)	[-5.92]	0.06	(0.94)	[0.95]	0.20
	1	0.04	(0.35)	[0.31]	-0.36	(-3.24)	[-2.93]	0.26	(3.34)	[3.17]	0.14
	2	0.07	(0.53)	[0.47]	-0.33	(-2.58)	[-2.24]	0.31	(4.03)	[3.55]	0.13
	4	0.16	(1.17)	[1.02]	-0.27	(-2.00)	[-1.79]	0.38	(3.98)	[3.56]	0.12
	8	0.32	(1.95)	[1.78]	-0.28	(-1.82)	[-1.67]	0.49	(4.42)	[4.16]	0.20
	20	0.39	(1.29)	[1.17]	-0.30	(-1.08)	[-0.88]	0.32	(2.59)	[2.99]	0.13
CF	0	0.20	(2.56)	[2.58]	-0.62	(-7.17)	[-7.23]	0.02	(0.30)	[0.30]	0.29
	1	0.16	(1.16)	[1.01]	-0.46	(-3.34)	[-2.92]	0.22	(2.81)	[2.56]	0.16
	2	0.18	(1.16)	[0.99]	-0.40	(-2.57)	[-2.18]	0.27	(3.46)	[3.00]	0.13
	4	0.26	(1.63)	[1.36]	-0.33	(-2.03)	[-1.74]	0.37	(4.13)	[3.68]	0.14
	8	0.38	(2.17)	[1.88]	-0.25	(-1.56)	[-1.45]	0.52	(5.16)	[4.91]	0.24
	20	0.35	(1.27)	[1.28]	0.05	(0.22)	[0.20]	0.27	(1.88)	[1.79]	0.16

Table I continued

$$y_{t,t+S} = b'_S z_t + e_{t,t+S} \text{ with } y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right) \text{ or } \sum_{s=1}^{S} CF_{t+s}$$

Panel B: Monthly data

		Dividend Yield			Default Spread			Term Spread			
	S	b_S	$t_{S,NW}$	$t_{S,HH}$	b_S	$t_{S,NW}$	$t_{S,HH}$	b_S	$t_{S,NW}$	$t_{S,HH}$	R^2
					Single predictive regressions						
IP	0	-0.12	(-2.66)	[-2.66]	-0.34	(-6.50)	[-6.51]	0.01	(0.16)	[0.16]	
	1	-0.13	(-2.30)	[-2.02]	-0.31	(-5.35)	[-4.80]	0.06	(1.41)	[1.28]	
	6	-0.14	(-1.35)	[-1.11]	-0.25	(-2.52)	[-2.15]	0.22	(2.46)	[2.01]	
	12	-0.06	(-0.49)	[-0.41]	-0.13	(-1.13)	[-1.00]	0.29	(2.81)	[2.37]	
	24	0.07	(0.47)	[0.40]	-0.04	(-0.30)	[-0.27]	0.37	(3.56)	[3.09]	
	60	0.14	(0.63)	[0.56]	-0.05	(-0.30)	[-0.28]	0.19	(1.23)	[1.29]	
CF	0	-0.10	(-1.96)	[-1.97]	-0.45	(-8.52)	[-8.53]	-0.05	(-1.31)	[-1.31]	
	1	-0.10	(-1.54)	[-1.30]	-0.41	(-5.87)	[-4.98]	0.02	(0.47)	[0.41]	
	6	-0.08	(-0.67)	[-0.53]	-0.29	(-2.48)	[-2.02]	0.17	(1.76)	[1.41]	
	12	0.00	(0.03)	[0.02]	-0.16	(-1.13)	[-0.98]	0.27	(2.54)	[2.13]	
	24	0.14	(0.82)	[0.70]	0.02	(0.10)	[0.11]	0.41	(4.21)	[4.23]	
	60	0.30	(1.43)	[1.68]	0.27	(1.80)	[1.83]	0.19	(1.47)	[1.74]	
					Multiple predictive regressions						
IP	0	0.08	(1.66)	[1.67]	-0.39	(-6.71)	[-6.73]	0.11	(2.65)	[2.66]	0.12
	1	0.08	(1.51)	[1.37]	-0.38	(-5.68)	[-5.12]	0.16	(3.50)	[3.19]	0.11
	6	0.11	(0.95)	[0.78]	-0.37	(-3.01)	[-2.53]	0.33	(4.30)	[3.57]	0.15
	12	0.17	(1.33)	[1.11]	-0.30	(-2.22)	[-1.95]	0.40	(4.43)	[3.78]	0.14
	24	0.33	(2.02)	[1.78]	-0.30	(-2.01)	[-1.76]	0.51	(4.76)	[4.32]	0.22
	60	0.38	(1.25)	[1.12]	-0.30	(-1.06)	[-0.86]	0.33	(2.57)	[2.85]	0.13
CF	0	0.20	(4.18)	[4.19]	-0.56	(-9.84)	[-9.86]	0.09	(2.42)	[2.42]	0.22
	1	0.20	(3.23)	[2.79]	-0.53	(-6.94)	[-5.95]	0.16	(3.26)	[2.82]	0.19
	6	0.22	(1.74)	[1.39]	-0.45	(-3.16)	[-2.56]	0.29	(3.82)	[3.13]	0.16
	12	0.28	(1.89)	[1.52]	-0.36	(-2.27)	[-1.91]	0.40	(4.54)	[3.89]	0.16
	24	0.40	(2.29)	[1.93]	-0.27	(-1.72)	[-1.53]	0.55	(5.57)	[5.08]	0.27
	60	0.34	(1.23)	[1.23]	0.05	(0.23)	[0.21]	0.27	(1.98)	[1.91]	0.17

Table II: Is exposure to DY, DS and TS priced among individual stocks? This table presents annualized average risk premiums from firm-level cross-sectional regressions for the asset-pricing model with DY, DS and TS as state variables over the period 1967.Q2 to 2011.Q4 (i.e., 179 quarterly and 537 monthly return observations). Row-wise I consider two-factor models that include each state variable next to the CRSP VW market portfolio as well as a joint four-factor model. Regressions of Type (A) include an intercept, whereas Type (B) does not. Panel A uses quarterly data, Panel B uses monthly data and Panel C replaces the $VAR(1)$-innovations in the state variables with their first-differences when estimating the first-stage betas. *, ** and *** indicate significance at the 10, 5 and 1%- level, respectively, using Fama and MacBeth (1973) standard errors. For the four-factor models, the t-statistics are also reported in parentheses. R^2 is the time-series average of the cross-sectional R_t^2's.

Model (A): $r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$; **Model (B)**: $r_{i,t+1} = \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	R^2
Panel A: Quarterly data						
(A) MKT+DY	8.38***	2.09	0.69			0.028
(A) MKT+DS	8.27***	1.33		-8.15***		0.030
(A) MKT+TS	7.97***	2.33			2.85	0.029
(A) MKT+DY+DS+TS	7.39***	1.49	0.37	-6.56***	5.79***	0.037
	(3.80)	(0.63)	(0.17)	(-2.75)	(3.20)	
(B) MKT+DY		7.99***	1.41			0.016
(B) MKT+DS		7.04**		-8.31***		0.018
(B) MKT+TS		7.74***			3.74*	0.019
(B) MKT+DY+DS+TS		6.61**	1.17	-6.35***	6.93***	0.026
		(2.43)	(0.47)	(-2.60)	(3.75)	
Panel B: Monthly data						
(A) MKT+DY	9.58***	0.30	3.45			0.021
(A) MKT+DS	9.27***	0.72		-6.18**		0.022
(A) MKT+TS	9.19***	0.81			3.48	0.022
(A) MKT+DY+DS+TS	8.23***	0.78	1.54	-5.28***	5.49***	0.027
	(5.13)	(0.32)	(0.54)	(-2.21)	(2.69)	
(B) MKT+DY		7.98***	4.55			0.015
(B) MKT+DS		7.97***		-5.44**		0.016
(B) MKT+TS		7.82***			6.06***	0.015
(B) MKT+DY+DS+TS		7.18***	3.43	-4.61*	7.62***	0.021
		(2.78)	(1.18)	(-1.92)	(3.77)	
Panel C: First-differences in state variables						
Quarterly data						
(A) MKT+DY+DS+TS	7.76***	1.09	-0.18	-5.47***	2.34	0.037
	(3.98)	(0.43)	(-0.07)	(-2.86)	(1.43)	
(B) MKT+DY+DS+TS		6.63**	-5.99**	-5.15***	4.16**	0.027
		(2.38)	(-2.24)	(-2.64)	(2.45)	
Monthly data						
(A) MKT+DY+DS+TS	8.34***	0.83	0.29	-4.93**	4.15**	0.026
	(5.08)	(0.30)	(0.11)	(-2.40)	(2.01)	
(B) MKT+DY+DS+TS		7.52***	-7.20***	-4.28**	7.07***	0.022
		(2.87)	(-2.80)	(-2.06)	(3.34)	

Table III: Predicting macroeconomic activity with alternative state variables

This table presents multiple regressions of macroeconomic activity (measured either with Industrial Production growth (IP) or the Chicago Fed National Activity Index (CF)) on alternative sets of ICAPM-motivated state variables. Model (1) replaces TS with RF. Model (2) includes RF (orthogonalized from TS) next to DY, DS and TS. Model (3) uses the state variables of Campbell and Vuolteenaho (2004): TS, PE and VS. Model (4) uses the state variables of Koijen et al. (2013): CP and LVL. (See Section B for a description of the variables.) The regressions use quarterly data and consider three horizons $S = 1, 4, 8$. *, ** and *** indicate significance at the 10%, 5% and 1%-level, respectively, using the more conservative Hansen and Hodrick (1980) asymptotic standard errors with S lags.

$$y_{t,t+S} = b'_S z_t + e_{t,t+S} \text{ with } y_{t,t+S} = \sum_{s=1}^{S} \log\left(\frac{IP_{t+s}}{IP_{t+s-1}}\right) \text{ or } \sum_{s=1}^{S} CF_{t+s}$$

	S	$b_{DY,S}$	$b_{DS,S}$	$b_{TS,S}$	$b_{RF,S}$ / $b_{RF\|TS,S}$	$b_{PE,S}$	$b_{VS,S}$	$b_{CP,S}$	$b_{LVL,S}$	R^2
					(1) $z_t = (DY_t, DS_t, RF_t)'$					
IP	1	-0.02	-0.27**		-0.07					0.09
	4	0.27	-0.14		-0.41***					0.10
	8	0.52**	-0.09		-0.61***					0.21
CF	1	0.04	-0.38**		0.01					0.12
	4	0.31	-0.24		-0.29					0.06
	8	0.52***	-0.13		-0.47**					0.12
					(2) $z_t = (DY_t, DS_t, TS_t, RF_t\|TS_t)'$					
IP	1	-0.05	-0.40***	0.24***	0.16					0.15
	4	0.25	-0.24	0.40***	-0.16					0.13
	8	0.49**	-0.20	0.54***	-0.32*					0.25
CF	1	-0.05	-0.47***	0.19**	0.29					0.20
	4	0.22	-0.33*	0.37***	0.05					0.13
	8	0.41**	-0.24	0.53***	-0.03					0.24
					(3) Campbell and Vuolteenaho (2004): $z_t = (TS_t, PE_t, VS_t)'$					
IP	1			0.20**		0.20*	-0.16**			0.06
	4			0.30**		0.09	-0.12			0.08
	8			0.36***		-0.08	0.02			0.12
CF	1			0.19*		0.20	-0.34***			0.09
	4			0.34***		0.06	-0.31***			0.14
	8			0.45***		-0.16	-0.16			0.21
					(4) Koijen et al. (2013): $z_t = (CP_t, LVL_t)'$					
IP	1							0.14	-0.15	0.03
	4							0.14	-0.22	0.05
	8							0.33***	-0.24*	0.14
CF	1							0.11	-0.01	0.01
	4							0.17*	-0.05	0.02
	8							0.40***	-0.04	0.15

Table IV: Firm-level risk premiums for alternative state variables
Row-wise this table presents annualized average risk premiums among individual stocks. Each quarter (Panel A) or month (Panel B) risk premiums are estimated with the two-stage cross-sectional regression method of Fama and MacBeth (1973). I consider multi-factor asset-pricing models that include the CRSP VW market portfolio and one of four different sets of ICAPM-motivated state variables z_t. In Model (1), I substitute RF for TS, such that $z_t = (DY_t, DS_t, RF_t)'$. In Model (2), I include both TS and RF, but orthogonalize RF from TS first, such that $z_t = (DY_t, DS_t, TS_t, RF_t|TS_t)'$. Model (3) follows Campbell and Vuolteenaho (2004) and defines $z_t = (TS_t, PE_t, VS_t)'$. Model (4) follows Koijen et al. (2013) and defines $z_t = (CP_t, LVL_t)'$. For each model, I present cross-sectional regressions with and without an intercept (Type (A) and (B), respectively). For each cross-sectional risk premium estimate, corresponding Fama and MacBeth (1973) t-statistics are presented underneath each estimate in parentheses. R^2 is the time-series average of the cross-sectional R_t^2.

Model (A): $r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$; **Model (B)**: $r_{i,t+1} = \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \upsilon_{i,t}$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	λ_{RF} / $\lambda_{RF\|TS}$	λ_{PE}	λ_{VS}	λ_{CP}	λ_{LVL}	R^2
					Panel A: Quarterly data						
(1.A)	7.87	1.34	-0.78	-7.70		-3.64					0.037
	(4.05)	(0.58)	(-0.37)	(-3.16)		(-1.77)					
(1.B)		6.90	-0.01	-7.70		-3.86					0.026
		(2.53)	(0.00)	(-3.04)		(-1.84)					
(2.A)	7.33	1.89	-1.13	-7.33	5.50	1.43					0.040
	(3.87)	(0.83)	(-0.58)	(-3.11)	(3.26)	(0.61)					
(2.B)		6.92	-0.50	-7.21	6.73	2.65					0.029
		(2.61)	(-0.23)	(-3.00)	(3.85)	(1.05)					
(3.A)	7.21	2.92			3.02		1.67	-5.23			0.036
	(3.77)	(1.19)			(1.59)		(0.82)	(-2.56)			
(3.B)		7.98			4.07		1.33	-5.50			0.026
		(2.80)			(2.10)		(0.63)	(-2.74)			
(4.A)	8.37	1.77							4.21	2.35	0.032
	(4.48)	(0.75)							(2.23)	(0.93)	
(4.B)		7.56							4.84	2.08	0.022
		(2.71)							(2.54)	(0.78)	
					Panel B: Monthly data						
(1.A)	8.38	0.89	-0.02	-6.00		-3.28					0.027
	(5.20)	(0.35)	(-0.01)	(-2.51)		(-1.45)					
(1.B)		7.47	1.69	-5.26		-4.94					0.022
		(2.85)	(0.57)	(-2.18)		(-2.20)					
(2.A)	8.27	0.66	-0.03	-5.65	5.09	1.64					0.029
	(5.17)	(0.27)	(-0.01)	(-2.45)	(2.61)	(0.77)					
(2.B)		6.99	1.59	-4.82	7.43	2.18					0.024
		(2.75)	(0.55)	(-2.08)	(3.79)	(1.01)					
(3.A)	8.40	1.33			3.85		2.99	-8.63			0.027
	(5.25)	(0.55)			(1.92)		(1.51)	(-3.44)			
(3.B)		7.89			5.95		3.80	-10.07			0.022
		(3.08)			(2.98)		(1.86)	(-3.91)			
(4.A)	9.25	0.57							5.85	1.07	0.025
	(5.68)	(0.23)							(2.64)	(0.43)	
(4.B)		7.79							7.03	-1.10	0.019
		(3.03)							(3.10)	(-0.44)	

Table V: Pre- and post-ranking analysis of DY, DS and TS mimicking portfolios

This table presents the portfolios that are implicit in the cross-sectional regression procedure, denoted FMB, in more detail. As a benchmark, the table also presents results for market value-weighted portfolios, that is, a one-dimensional sort in five quintiles (MV, H to MV, L) as well as the resulting spreading portfolio ($HLMV$), and an equal-weighted spreading portfolio ($HLEW$). Panel A presents (i) post-ranking exposures $(\beta_m, \delta')'$ from the four-factor model $r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon^{Full}_{DY_t}, \varepsilon^{Full}_{DS_t}, \varepsilon^{Full}_{TS_t})' + u_t$, (where standard errors are Newey-West with lag length one), (ii) average pre-ranking exposure within the portfolio, and (iii) annualized performance (average return, standard deviation and Sharpe ratio). Panel B focuses solely on the three mimicking strategies and presents pre-ranking characteristics: Size ($ billion), Book-to-Market and Momentum, which are weighted cross-sectional averages (and where standard errors are Newey-West with lag length ten), as well as HH, which is a cross-sectional Herfindahl-index, and annualized Turnover. Wherever necessary *, ** and *** indicate significance at the 10, 5 and 1% -level, respectively.

Panel A: Exposures and unconditional performance

	Post-ranking exposures						Pre-rank.	Avg.	St.	Sharpe
	α	β_m	δ_{DY}	δ_{DS}	δ_{TS}	R^2	exposure	ret.	dev.	ratio
				Dividend Yield mimicking portfolios						
MV, H	0.00	1.31***	0.22***	0.03	-0.12***	0.87	0.52	6.55*	25.76	0.25
$MV, 2$	0.00	1.07***	0.02	0.03	-0.01	0.90	0.21	7.14**	20.26	0.35
$MV, 3$	0.00	0.93***	0.01	0.04**	0.02*	0.94	0.05	5.89**	17.30	0.34
$MV, 4$	0.00**	0.85***	-0.04**	-0.02	0.00	0.93	-0.10	5.89**	15.90	0.37
MV, L	0.00	1.01***	-0.01	-0.02	0.02	0.88	-0.36	6.70**	19.32	0.35
$HLMV$	0.00	0.30***	0.22***	0.05	-0.14***	0.23	0.88	-0.15	14.96	-0.01
$HLEW$	0.00	0.09*	0.11*	0.06	-0.03	0.05	0.99	0.65	10.85	0.06
FMB	0.00	0.16**	0.29***	-0.04	0.00	0.17	1.00	0.37	14.43	0.03
				Default Spread mimicking portfolios						
MV, H	0.00	1.03***	0.10**	0.06**	-0.06*	0.88	0.32	5.77*	19.87	0.29
$MV, 2$	0.00	0.89***	0.00	0.02	0.04	0.94	0.05	5.08**	16.53	0.31
$MV, 3$	0.00**	0.94***	-0.05	0.01	0.00	0.89	-0.12	6.95***	17.94	0.39
$MV, 4$	0.01**	1.11***	0.00	0.01	0.03	0.87	-0.29	8.25***	21.41	0.39
MV, L	0.00	1.31***	0.10*	-0.05	0.06	0.82	-0.62	7.61*	26.05	0.29
$HLMV$	0.00	-0.28***	0.01	0.11**	-0.12*	0.12	0.94	-1.84	15.20	-0.12
$HLEW$	-0.01**	-0.17**	0.03	0.08**	-0.03	0.05	1.02	-4.59**	12.97	-0.35
FMB	-0.01***	-0.21**	-0.02	0.32**	-0.04	0.17	1.00	-6.56***	15.93	-0.41
				Term Spread mimicking portfolios						
MV, H	0.01	1.13***	0.10*	-0.09**	0.11***	0.80	0.60	8.02**	22.95	0.35
$MV, 2$	0.01*	1.01***	0.03	-0.01	0.04	0.88	0.29	7.55***	19.40	0.39
$MV, 3$	0.00	0.93***	-0.04	0.00	0.04**	0.92	0.11	5.83**	17.32	0.34
$MV, 4$	0.00	0.93***	-0.01	0.05***	-0.03	0.93	-0.05	4.99*	17.32	0.29
MV, L	-0.01**	1.05***	0.06	0.03	-0.05**	0.87	-0.30	3.13	20.18	0.16
$HLMV$	0.01*	0.08	0.04	-0.11**	0.16***	0.04	0.90	4.90**	14.50	0.34
$HLEW$	0.02***	-0.05	-0.04	-0.05	0.10**	0.03	1.02	5.62***	10.35	0.54
FMB	0.01***	-0.02	-0.02	0.02	0.17**	0.06	1.00	5.79***	12.12	0.48

Table V continued

Panel B: Pre-ranking portfolio characteristics

	Size	Book-to-Market	Momentum	HH	Turnover
		Dividend Yield mimicking portfolios			
HLMV	-16.23**	0.10*	6.92	0.062	1.673
HLEW	-0.96***	0.11*	1.54	0.004	1.837
FMB	-1.38***	0.13*	4.92	0.008	1.482
		Default Spread mimicking portfolios			
HLMV	8.19	-0.20**	-9.79	0.074	1.595
HLEW	0.91***	-0.36***	0.01	0.004	1.702
FMB	1.13***	-0.43***	2.45	0.006	1.492
		Term Spread mimicking portfolios			
HLMV	-8.46	0.20***	0.44	0.070	1.556
HLEW	-1.29***	0.17***	-0.26	0.004	1.746
FMB	-0.82***	0.15***	1.93	0.009	1.460

Table VI: Mimicking portfolios for alternative state variables
This table presents the portfolios that are implicit in the cross-sectional regression procedure, denoted FMB, and the benchmark spreading portfolios ($HLMV$ and $HLEW$) for the alternative sets of state variables. Panel A presents results for the model where $z_t = (DY_t, DS_t, RF_t)'$; Panel B for $z_t = (TS_t, PE_t, VS_t)'$ as in Campbell and Vuolteenaho (2004); and, Panel C for $z_t = (CP_t, LVL_t)'$ as in Koijen et al. (2013). Focusing solely on the mimicking portfolios for the alternative state variables that are priced in Table IV: RF, PE, VS, CP and LVL, I report (i) post-ranking exposures $(\beta_m, \delta')'$ from the model $r_{p,t} = \alpha + \beta_m r_{m,t} + \delta' \varepsilon_{z_t}^{Full} + u_t$, (where standard errors are Newey-West with lag length one) and (ii) annualized performance (average return, standard deviation and Sharpe ratio). *, ** and *** indicate significance at the 10, 5 and 1%- level, respectively.

Panel A: $z_t = (DY_t, DS_t, RF_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{DY_t}^{Full}, \varepsilon_{DS_t}^{Full}, \varepsilon_{RF_t}^{Full})' + u_t$						Avg.	St.	Sharpe
	α	β_m	δ_{DY}	δ_{DS}	δ_{RF}	R^2	ret.	dev.	ratio
				RF mimicking portfolios					
HLMV	-0.01**	-0.09	0.01	0.00	0.16**	0.03	-4.59**	14.09	-0.33
HLEW	-0.02***	-0.01	0.06	0.01	0.12*	0.03	-6.34***	11.15	-0.57
FMB	-0.01**	0.09	0.02	-0.02	0.20**	0.08	-3.64*	13.79	-0.26

Panel B: Campbell and Vuolteenaho (2004): $z_t = (TS_t, PE_t, VS_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{TS_t}^{Full}, \varepsilon_{PE_t}^{Full}, \varepsilon_{VS_t}^{Full})' + u_t$						Avg.	St.	Sharpe
	α	β_m	δ_{TS}	δ_{PE}	δ_{VS}	R^2	ret.	dev.	ratio
				PE mimicking portfolios					
HLMV	0.00	-0.02	0.04	0.05	-0.20***	0.06	-0.56	13.59	-0.04
HLEW	0.00	0.03	-0.02	0.08*	-0.09	0.02	0.44	11.29	0.04
FMB	0.01	-0.04	-0.04	0.19**	-0.11	0.07	1.67	13.57	0.12
				VS mimicking portfolios					
HLMV	-0.01	0.35***	-0.12*	0.01	0.21**	0.18	-1.72	17.53	-0.10
HLEW	-0.01***	0.20***	-0.03	-0.04	0.11	0.12	-3.79**	11.20	-0.34
FMB	-0.02***	0.24***	-0.03	-0.05	0.10	0.11	-5.23**	13.67	-0.38

Panel C: Koijen et al. (2013): $z_t = (CP_t, LVL_t)'$

	$r_{p,t} = \alpha + \beta_m r_{m,t} + \delta'(\varepsilon_{CP_t}^{Full}, \varepsilon_{LVL_t}^{Full})' + u_t$					Avg.	St.	Sharpe
	α	β_m	δ_{CP}	δ_{LVL}	R^2	ret.	dev.	ratio
				CP mimicking portfolios				
HLMV	0.00	0.31***	0.12***	0.05	0.17	3.24	14.15	0.23
HLEW	0.01	0.11*	0.03	0.01	0.02	2.98*	10.62	0.28
FMB	0.01**	0.02	0.07	-0.08	0.01	4.21**	12.60	0.33
				LVL mimicking portfolios				
HLMV	-0.01	0.55***	0.12**	0.31***	0.39	0.98	18.12	0.05
HLEW	0.00	0.36***	0.08	0.23***	0.29	1.41	14.06	0.10
FMB	0.00	0.34***	0.11	0.32***	0.24	2.35	16.90	0.14

Table VII: Are DY, DS and TS risk premiums captured by the factors and characteristics of Fama and French (1992, 1993)?

This table analyzes whether the risk premiums for DY, DS and TS can be captured by the benchmark factors SMB and HML (and MOM) as well as their underlying characteristics Size and Book-to-Market (and Prior return). To this end, Panel A presents time-series regressions of the Fama and MacBeth (1973) cross-sectional regression risk premiums (from Table II) on the Fama and French (1993) three-factor model (FF3M) as well as the Carhart (1997) four-factor model (FFCM) using both quarterly and monthly data. t-statistics based on Newey-West standard errors with lag length one are in parentheses. Next, I present cross-sectional regressions that additionally include the benchmark factors and characteristics at the quarterly frequency (Panel B) and the monthly frequency (Panel C). Model (1) presents results for the FF3M. Model (2) adds the state variables. Model (3) adds the state variables to the characteristics Size and Book-to-Market instead. Model (4) includes the state variables, SMB, HML, Size and Book-to-Market. Model (5) adds to this model the MOM factor and the Momentum characteristic. Throughout, Type (A) includes an intercept, whereas Type (B) restricts the intercept to zero. For each cross-sectional regression, the table presents the unconditional average annualized risk premiums $\lambda = \frac{1}{T}\sum\limits_{t}\widehat{\lambda}_t$, with Fama and MacBeth (1973) $t-$statistics in parentheses, and the average cross-sectional $R^2 = \frac{1}{T}\sum\limits_{t} R_t^2$.

Panel A: Time-series regressions

$$r_{FMB(k),t} = \alpha + \beta_m r_{m,t} + \beta_{smb} r_{smb,t} + \beta_{hml} r_{hml,t} + (\beta_{mom} r_{mom,t}) + \varepsilon_t$$

Quarterly data						Monthly data					
α	β_m	β_{smb}	β_{hml}	β_{mom}	R^2	α	β_m	β_{smb}	β_{hml}	β_{mom}	R^2
Dividend Yield mimicking portfolio ($FMB(DY)$)											
0.25	0.02	0.34	-0.19		0.10	1.03	0.10	0.46	-0.27		0.14
(0.13)	(0.24)	(2.43)	(-1.82)			(0.37)	(1.44)	(3.72)	(-2.05)		
1.69	0.00	0.30	-0.23	-0.12	0.11	4.26	0.05	0.46	-0.37	-0.29	0.19
(0.76)	(-0.02)	(2.11)	(-2.11)	(-1.26)		(1.31)	(0.70)	(4.04)	(-2.77)	(-2.19)	
Default Spread mimicking portfolio ($FMB(DS)$)											
-2.89	-0.12	-0.56	-0.32		0.22	-2.22	-0.14	-0.58	-0.17		0.19
(-1.38)	(-1.15)	(-5.44)	(-2.60)			(-1.01)	(-2.32)	(-6.35)	(-1.64)		
-5.26	-0.08	-0.49	-0.26	0.20	0.25	-4.38	-0.11	-0.57	-0.11	0.20	0.23
(-1.27)	(-1.03)	(-3.73)	(-2.09)	(0.86)		(-1.75)	(-1.90)	(-6.76)	(-1.18)	(2.30)	
Term Spread mimicking portfolio ($FMB(TS)$)											
4.20	0.06	-0.05	0.29		0.06	3.10	-0.03	0.18	0.45		0.11
(2.33)	(0.85)	(-0.50)	(2.94)			(1.49)	(-0.47)	(2.29)	(4.26)		
4.72	0.05	-0.07	0.28	-0.04	0.06	3.76	-0.04	0.18	0.43	-0.06	0.12
(2.78)	(0.76)	(-0.65)	(2.87)	(-0.58)		(1.78)	(-0.68)	(2.28)	(4.19)	(-1.20)	

Table VII continued

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \lambda'_{f,t}(\widehat{\beta_{i,smb,t}}, \widehat{\beta_{i,hml,t}}, \widehat{\beta_{i,mom,t}})' + \lambda'_{c,t}(Size_{i,t}, BM_{i,t}, PRET_{i,t})' + \upsilon_{i,t}$$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	λ_{smb}	λ_{hml}	λ_{mom}	λ_{Size}	λ_{BM}	λ_{PRET}	R^2
Panel B: Cross-sectional regressions - Quarterly data												
(1.A)	6.95	1.58				1.91	2.63					0.042
	(3.77)	(0.67)				(1.24)	(2.03)					
(1.B)		6.54				3.33	2.03					0.035
		(2.54)				(2.04)	(1.54)					
(2.A)	6.69	1.78	0.39	-5.58	4.20	2.17	2.24					0.048
	(3.58)	(0.82)	(0.22)	(-2.52)	(2.61)	(1.41)	(1.78)					
(2.B)		6.56	0.60	-5.21	4.95	3.57	1.64					0.040
		(2.64)	(0.30)	(-2.41)	(3.05)	(2.16)	(1.29)					
(3.A)	7.50	2.59	-1.34	-1.77	4.28				-3.23	2.96		0.059
	(3.74)	(1.22)	(-0.71)	(-1.06)	(2.79)				(-2.72)	(4.35)		
(3.B)		7.68	-0.22	-2.30	5.08				-2.87	3.22		0.049
		(2.75)	(-0.10)	(-1.20)	(3.26)				(-2.52)	(4.73)		
(4.A)	7.17	3.58	-0.80	-1.92	3.32	0.39	0.18		-3.53	2.68		0.066
	(3.69)	(1.72)	(-0.47)	(-1.13)	(2.29)	(0.33)	(0.16)		(-3.12)	(4.21)		
(4.B)		8.42	-0.10	-2.25	3.78	2.06	-0.24		-3.22	2.86		0.057
		(3.20)	(-0.05)	(-1.21)	(2.59)	(1.49)	(-0.21)		(-2.92)	(4.55)		
(5.A)	7.98	2.56	-0.02	-2.56	2.54	0.56	-0.26	-2.20	-3.61	2.75	0.87	0.073
	(3.81)	(1.38)	(-0.01)	(-1.79)	(2.00)	(0.51)	(-0.26)	(-2.02)	(-3.38)	(4.42)	(1.04)	
(5.B)		7.95	1.10	-3.35	3.17	2.53	-0.58	-3.20	-3.11	2.96	0.42	0.065
		(3.07)	(0.61)	(-1.87)	(2.55)	(1.83)	(-0.54)	(-2.52)	(-3.03)	(4.76)	(0.54)	
Panel C: Cross-sectional regressions - Monthly												
(1.A)	8.09	-0.12				1.70	3.16					0.035
	(5.50)	(-0.05)				(1.12)	(2.12)					
(1.B)		6.28				2.97	3.12					0.031
		(2.63)				(1.90)	(2.08)					
(2.A)	7.66	0.12	0.39	-4.56	3.46	1.62	2.93					0.040
	(5.18)	(0.05)	(0.16)	(-2.42)	(1.91)	(1.08)	(2.03)					
(2.B)		6.15	1.71	-4.05	4.64	2.85	2.89					0.036
		(2.60)	(0.67)	(-2.15)	(2.58)	(1.84)	(1.99)					
(3.A)	7.27	2.81	0.97	-0.33	2.84				-4.11	2.55		0.044
	(4.57)	(1.19)	(0.38)	(-0.18)	(1.65)				(-3.77)	(4.67)		
(3.B)		8.32	2.61	-0.05	4.77				-4.03	2.76		0.039
		(3.15)	(1.00)	(-0.03)	(2.69)				(-3.76)	(4.90)		
(4.A)	7.39	4.34	1.28	-1.44	2.59	-1.89	0.14		-4.85	2.35		0.050
	(4.91)	(1.96)	(0.54)	(-0.84)	(1.58)	(-1.54)	(0.11)		(-4.81)	(5.11)		
(4.B)		10.06	2.77	-1.26	3.69	-0.67	0.17		-4.85	2.38		0.047
		(4.12)	(1.12)	(-0.73)	(2.22)	(-0.52)	(0.12)		(-4.86)	(5.24)		
(5.A)	7.97	4.09	2.14	-1.67	2.36	-2.23	-0.27	-2.56	-5.41	2.29	2.59	0.057
	(5.14)	(1.98)	(1.00)	(-1.01)	(1.60)	(-1.88)	(-0.22)	(-1.81)	(-5.68)	(4.98)	(4.11)	
(5.B)		10.31	3.85	-1.61	3.52	-0.82	-0.23	-3.18	-5.36	2.35	2.38	0.054
		(4.36)	(1.74)	(-0.95)	(2.38)	(-0.65)	(-0.18)	(-2.15)	(-5.68)	(5.16)	(3.90)	

Table VIII: Are risk premiums for the alternative state variables captured by the factors and characteristics of Fama and French (1992, 1993)?

This table analyzes whether the firm-level risk premiums for exposure to the alternative state variables are captured by exposure to the benchmark factors (SMB and HML) or their underlying characteristics (Size and Book-to-Market) at the quarterly frequency (Panel A) and the monthly frequency (Panel B). Row-wise the triplet (a,b,c) defines the specification. "a" defines the set of state variables included next to the CRSP VW market return: (1) $z_t = (DY_t, DS_t, RF_t)'$; (2) $z_t = (DY_t, DS_t, TS_t, RF_t|TS_t)'$; (3) $z_t = (TS_t, PE_t, VS_t)'$ as in Campbell and Vuolteenaho (2004); and, (4) $z_t = (CP_t, LVL_t)'$ as in Koijen et al. (2013). "b" defines the whether an intercept is included (A) or not (B). "c" defines the benchmark variables that are included, that is, either (I) exposures to SMB and HML or (II) both exposures to SMB and HML and characteristics Size and Book-to-Market . For each cross-sectional regression, the table presents the annualized unconditional average risk premium $\lambda = \frac{1}{T}\sum_t \widehat{\lambda}_t$ (where *, ** and *** indicate significance at the 10, 5 and 1%-level, respectively, using Fama and MacBeth (1973) standard errors) and R^2, which is the time-series average of the cross-sectional R^2_t.

Panel A: Quarterly data

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \lambda'_{f,t}(\widehat{\beta_{i,smb,t}}, \widehat{\beta_{i,hml,t}})' + \lambda'_{c,t}(Size_{i,t}, BM_{i,t})' + v_{i,t}$$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	$\lambda_{RF}/\lambda_{RF\|TS}$	λ_{PE}	λ_{VS}	λ_{CP}	λ_{LVL}	λ_{smb}	λ_{hml}	λ_{Size}	λ_{BM}	R^2
(1.A.I)	6.80***	1.66	-0.57	-6.28***		-2.82					2.10	2.22*			0.047
(1.B.I)		6.59***	-0.57	-6.00***		-2.91					3.46**	1.65			0.040
(1.A.II)	7.30***	3.45*	-1.85	-2.58		-2.24					0.32	0.10	-3.55***	2.74***	0.065
(1.B.II)		8.45***	-1.37	-3.02		-1.94					1.98	-0.30	-3.23***	2.90***	0.057
(2.A.I)	6.72***	1.74	-0.93	-5.85***	4.62***	1.58					2.16	2.13*			0.050
(2.B.I)		6.52***	-0.89	-5.50**	5.49***	2.54					3.57**	1.56			0.042
(2.A.II)	7.45***	3.42*	-2.27	-2.35	3.68**	0.92					0.30	0.01	-3.65***	2.73***	0.067
(2.B.II)		8.43***	-1.76	-2.73	4.25***	2.12					2.06	-0.39	-3.31***	2.89***	0.059
(3.A.I)	6.56***	2.03			2.48		0.45	-3.18*			2.02	2.37*			0.048
(3.B.I)		6.77***			3.32**		0.35	-3.45**			3.39**	1.67			0.040
(3.A.II)	7.06***	3.79*			1.78		0.54	-1.10			0.30	0.24	-3.56***	2.62***	0.066
(3.B.II)		8.67***			2.25		0.46	-1.53			1.91	-0.27	-3.26***	2.81***	0.058
(4.A.I)	6.80***	1.67							2.49	0.91	2.09	2.49*			0.046
(4.B.I)		6.39**							2.71*	0.46	3.59**	1.96			0.039
(4.A.II)	7.24***	3.57*							1.11	-0.48	0.33	0.39	-3.63***	2.69***	0.064
(4.B.II)		8.33***							1.28	-0.31	2.11	0.03	-3.28***	2.87***	0.056

Table VIII continued

Panel B:Monthly data

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{m,t}\widehat{\beta_{i,m,t}} + \lambda'_{z,t}\widehat{\delta_{i,t}} + \lambda'_{f,t}(\widehat{\beta_{i,smb,t}}, \widehat{\beta_{i,hml,t}})' + \lambda'_{c,t}(Size_{i,t}, BM_{i,t})' + \upsilon_{i,t}$$

	λ_0	λ_m	λ_{DY}	λ_{DS}	λ_{TS}	$\lambda_{RF}/\lambda_{RF\|TS}$	λ_{PE}	λ_{VS}	λ_{CP}	λ_{LVL}	λ_{smb}	λ_{hml}	λ_{Size}	λ_{BM}	R^2
(1.A.I)	7.77***	0.13	-1.31	-5.05***		-1.82					1.59	2.92**			0.040
(1.B.I)		6.27***	-0.29	-4.51**		-2.83					2.78*	2.85*			0.037
(1.A.II)	7.55***	4.30*	-0.80	-1.79		-2.51					-1.96	0.08	-4.90***	2.39***	0.051
(1.B.II)		10.16***	0.40	-1.60		-3.43**					-0.76	0.07	-4.90***	2.42***	0.047
(2.A.I)	7.83***	0.02	-0.93	-4.68**	3.41*	1.98					1.43	2.90**			0.041
(2.B.I)		6.16***	0.12	-4.15**	4.72***	2.12					2.66*	2.84*			0.038
(2.A.II)	7.63***	4.23*	-0.22	-1.73	2.55	-0.48					-2.09*	0.05	-4.87***	2.41***	0.052
(2.B.II)		10.12***	1.05	-1.54	3.77**	-0.34					-0.85	0.06	-4.86***	2.44***	0.048
(3.A.I)	8.13***	-0.24			2.62		0.55	-7.06***			1.68	3.21**			0.038
(3.B.I)		6.17***			3.81**		0.82	-7.53***			3.02*	3.15**			0.035
(3.A.II)	7.68***	4.09*			1.57		-0.40	-4.97**			-1.80	0.43	-4.89***	2.27***	0.050
(3.B.II)		10.01***			2.69		-0.16	-5.39***			-0.47	0.40	-4.89***	2.33***	0.046
(4.A.I)	8.09***	-0.10							3.43**	0.53	1.74	3.10**			0.038
(4.B.I)		6.26***							3.64**	-1.36	3.08**	3.01**			0.035
(4.A.II)	7.79***	4.15*							1.60	-1.68	-1.90	0.32	-5.00***	2.23***	0.049
(4.B.II)		10.17***							1.72	-3.46*	-0.54	0.25	-4.97***	2.32***	0.046

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